Common Ingroup Identity and Racial Minority Political Solidarity

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Abstract

Identification with a common ingroup has been shown to reduce prejudice against former outgroup members who are included in the common ingroup, but some research suggests that prejudice reduction interventions, including common ingroup identity, can have a “paradoxical” effect on minority group members of reducing their support for social change that would improve their group’s situation. These paradoxical effects stand in contrast to research on collective action and group consciousness suggesting that identification with a disadvantaged group predicts increases in collective action and political behavior on behalf of the group. In two 3-wave panel studies, using cross-lagged panel models (CLPM) and random-intercepts cross-lagged panel models (RI-CLPM), I examined whether identification with a common ingroup that includes Whites (American identity) and identification with a common ingroup that does not include Whites (person of color, or POC, identity) have different effects on racial minorities’ attitudes toward other racial minority groups and policies that benefit racial minority groups. I generally found trait-level correlations that were consistent with the literature on common ingroup identity, paradoxical effects, collective action, and group consciousness: Among Asian (Study 1), Black (Study 2), and Latino (Study 2) Americans, common ingroup identities (American and POC) were positively associated with attitudes toward other racial groups included in the common ingroup, American identity was generally negatively associated with attitudes toward policies that benefit other minority groups, and disadvantaged group identities (racial and POC) were generally positively associated with attitudes toward policies that benefit minority groups. But except for POC identity and Asian

Americans' stereotype ratings of other minority groups and support for affirmative action (Study 1), I did not find consistent cross-lagged effects. Thus, these studies offer little support for the theory that identity predicts (and potentially causes) attitude *change*, at least among minority American adults.

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Chapter 1: Introduction & Literature Review

As the United States moves toward becoming a “majority minority” nation, research on racial attitudes and intergroup relations still tends to focus on the attitudes and behaviors of Whites and the impact of these attitudes and behaviors on minorities. Relatively little research examines racial minorities as active participants in the social and political system. Specifically, only recently have social or political psychologists begun to study whether and under what circumstances racial and ethnic minority groups behave as if they were part of a unified social or political group (e.g., Craig & Richeson, 2012). In this respect, Asian Americans in particular, having been positioned historically as “definitively not-black model minorities” (Wu, 2014, p. 149) or “racially triangulated vis-à-vis Blacks and Whites” (i.e., their status in society is defined in comparison to both Whites and Blacks; Kim, 1999, p. 107), might view themselves as separate from other minority groups and hold negative attitudes toward those groups. Racial triangulation, along with other, less deliberate differences in the historical experiences of different minority groups, suggests that racial minority groups might not always (or even usually) show solidarity with each other and that patterns of solidarity might differ across minority groups. Studying these patterns of solidarity or lack thereof is important to understanding what becoming a “majority minority” nation actually means.

Until recently, social psychologists studying racial attitudes have tended to focus on changing the attitudes of (individual) dominant or majority group[1] members in an

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[1] Although the term “dominant group” refers to group power and the term “majority group” refers to group size, and although in some contexts, the dominant group is a minority group, my research focuses on racial groups in the United States, where the dominant group—Whites—has historically been and currently still is the majority group.

effort to reduce prejudice (Dixon et al., 2012; Reicher, 2007). Within this literature, two particularly effective interventions for reducing dominant group members' prejudice against subordinate groups have been intergroup contact (Pettigrew & Tropp, 2006) and recategorization into a common ingroup identity (e.g., Gaertner & Dovidio, 2005). But how do these theories and findings apply to inter-minority attitudes and group relations?

Focusing on the common ingroup identity model (CIIM), I posit that identifying with a common ingroup has different effects on minority group members depending on whether or not the common ingroup includes the majority group (i.e., Whites). Accordingly, I examine two forms of common ingroup identity that are available to racial minorities in the United States: American identity, which includes other racial minorities and Whites, and person of color (POC)[2] identity, which includes other racial minorities but not Whites. Both forms of common ingroup identity should predict more positive attitudes toward other minority groups, who are included in both common ingroups. But common ingroups that do and do not include the majority group should have different effects on support for social change that challenges the existing group hierarchy. Specifically, a recent line of research found that common ingroup identity can have a "paradoxical" effect (e.g., Dixon, Durrheim, et al., 2010) of reducing subordinate group

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Thus, I use the terms dominant group and majority group interchangeably and the terms subordinate group and minority group interchangeably (see Dovidio et al., 2016 for similar usage of "majority" and "minority" group labels).

[2] I am aware that "BIPOC" has superseded "POC" in some circles and that different labels for racial minority common ingroups (e.g., "POC/BIPOC" vs. "racial minority" vs. "nonwhite" vs. "Black and brown") might have somewhat different implications for who self-identifies as a group member and who is perceived as a group member. I chose "POC" as a term that had been in common use across racial groups for some time and thus would likely be recognized by most respondents. Whether differences in the group label affect the identity-attitude relationships I study might be a topic for future research.

members' support for social change that would improve their group's situation (e.g., Ufkes et al., 2016; Dovidio et al., 2016). I hypothesize that these paradoxical effects occur only when the dominant group is part of the common ingroup.

By contrast, research on collective action (e.g., van Zomeren, Postmes, & Spears, 2008) and group consciousness (e.g., Miller et al., 1981) connects identification with a disadvantaged group to increases in collective action and political behavior on behalf of the group. As a disadvantaged group identity, a common ingroup identity that does not include the dominant group might increase support for social change through similar processes. In other words, a common ingroup identity that does not include the dominant group could function more like a subgroup identity than a traditional common ingroup identity in predicting policy attitudes and support for change.

Additionally, most of the existing CIIM research involves experimental manipulations of identity salience, but much of the research on political attitudes and collective action uses survey measures of identity. To extend the external validity of the CIIM and connect it to research on collective action and political attitudes, I use a 3-wave panel survey design in which group identification (which theoretically relates to chronic identity salience; see, e.g., Wright, 2010), racial attitudes, and support for policies and groups that challenge the racial status quo are measured over time. Because these dynamics might differ by race as a consequence of the historical experiences of different minority racial and ethnic groups, I separately analyze data from Asian (Study 1), Latino (Study 2), and Black respondents (Study 2).

In the rest of this chapter, I review the relevant literature from social and political psychology. Chapter 2 provides an overview of my studies and a summary of my hypotheses as applied to each study. Chapters 3 and 4 describe Studies 1 and 2, respectively. Chapter 5 discusses my overall findings in the context of the existing literature, including theoretical and practical implications, limitations, and future research directions.

This chapter reviews the literature as follows: Section A introduces the prejudice reduction framework and the common ingroup identity model, as well as the potential for prejudice reduction strategies to have paradoxical effects on subordinate group members. Section B discusses theories of collective action, their bases in social identity theory and self-categorization theory, and their proposed mechanisms for the relationship between group identification and support for collective action. Section C considers group consciousness and linked fate as potential mediators of the relationship between group identity and political attitudes. Sections D through F lay out my reasoning for my proposed measures of identity and potential mediators, the 3-wave panel design, and the focus on Asian Americans in my main study (Study 1). Section G integrates the earlier sections, as well as observations about what policy areas might be perceived as affecting which racial groups, to make specific predictions for Asian, Latino, and African American respondents.

A. Prejudice Reduction and Common Ingroup Identity

Questions about the nature and origins of prejudice have been a major theme of social psychology since the middle of the twentieth century (see, e.g., Allport, 1954; Adorno et al., 1950). Building on Allport's (1954) ideas, researchers began to focus on prejudiced individual members of dominant groups and how to reduce these individuals' prejudice (Reicher, 2007). Prejudice, in this framework, tends to be defined as negative attitudes toward outgroup members (Dixon et al., 2012), with no explicit distinction between dominant group members' attitudes toward subordinate group members and subordinate group members' attitudes toward dominant group members.

If prejudiced individuals are the problem, prejudice reduction is the logical goal. Thus, social psychologists have studied a myriad of interventions to reduce prejudice (Paluck & Green, 2009; see also Lai et al., 2014, for interventions aimed at reducing implicit prejudice). One of the most successful prejudice reduction interventions studied to date has been intergroup contact (Pettigrew & Tropp, 2006). Intergroup contact would ideally take place under four conditions attributed to Allport: equal status in the contact situation, shared goals, intergroup cooperation to achieve those goals, and support from authorities, but prejudice reduction occurs even when the conditions are not met (Pettigrew & Tropp, 2006).

However, intergroup contact tends to have smaller effects on minority group members than on majority group members (Tropp & Pettigrew, 2005). Additionally, the effects of inter-minority group contact are relatively under-studied, and existing research suggests that relative status between the minority groups (Bikmen, 2011) and contact with the majority group (cf. Glasford & Calcagno, 2012) might moderate these effects.

1. Social Identity as a Target for Prejudice Reduction

Social identity theory (SIT) suggests a potential origin for prejudice that can be targeted for prejudice reduction. Studies using the minimal group paradigm showed that merely categorizing people into groups can produce behaviors that favor the ingroup over the outgroup (e.g., Tajfel et al., 1971). Tajfel and Turner (1979) introduced the concept of social identity, defined as "those aspects of an individual's self-image that derive from the social categories to which he perceives himself as belonging," to explain these findings (p. 40). They proposed that 1) people strive for positive self-concepts and thus strive for positive social identities, and 2) the positivity or negativity of social identity depends on comparisons with relevant outgroups (Tajfel & Turner, 1979). As a result, if an individual identifies with an ingroup and is in a situation that allows comparison with a relevant outgroup, they will be motivated to engage in intergroup competition to positively distinguish the ingroup from the outgroup (Tajfel & Turner, 1979). To reduce the kinds of ingroup bias that are driven by social identity processes, then, one could imagine either reducing ingroup identification (or its relevance to the situation) or reducing the potential for intergroup comparisons (e.g., by not having a relevant outgroup available).

Decategorization (prompting people to think of themselves as individuals) and recategorization (prompting people to think of themselves as part of a common ingroup) use these insights, along with the idea from self-categorization theory that the self can be defined at multiple levels of inclusiveness (Turner & Reynolds, 2012), to reduce prejudice. Decategorization makes ingroup identification irrelevant to the situation and thus reduces the positivity of evaluations of ingroup members; recategorization redefines outgroup members as part of a common ingroup and thus extends the processes of ingroup favoritism to those former outgroup members (Gaertner et al., 1989). Recategorization into a common ingroup has been shown to improve attitudes toward former outgroup members (Gaertner et al., 1989) and increase willingness to help former outgroup members (Dovidio et al., 1997), among other benefits.

Additionally, the common ingroup identity model (CIIM) provides a potential mechanism for the prejudice reduction effects of intergroup contact (Dovidio et al., 2016). According to Dovidio et al. (2016), Allport's optimal contact conditions tend to create feelings of being part of a common group, and stronger one-group feelings in intergroup contact studies are associated with reduced bias and intergroup anxiety. For example, a recent study involving an "us" or "not us" categorization task provides evidence that something like a common ingroup identity (what the authors refer to as a "more inclusive social identity") might underlie the effects of at least intergroup friendship (Reimer et al., 2020).

Common ingroup identity has also been proposed as a mechanism through which racial minorities' experiences of discrimination promote more positive attitudes toward other racial minority groups (Craig & Richeson, 2012). Craig and Richeson's (2012) findings suggest that CIIM can apply to inter-minority group relations as well as traditional majority-minority group relations.

2. Paradoxical Effects of Prejudice Reduction

Even if prejudice reduction interventions improve intergroup attitudes across the board, however, they might have unintended consequences for members of subordinate groups. A relatively recent line of research suggests that intergroup contact and common ingroup identity can reduce subordinate group members' recognition of inequality (e.g., Tropp et al., 2012; Ufkes et al., 2016) and, consequently, their support for collective action or policies that could improve their group's status (e.g., Saguy et al., 2009; Ufkes et al., 2016; Carter et al., 2019). Earlier research on the group-value model of justice similarly hinted that superordinate group identification could have a pacifying effect on members of disadvantaged groups by prompting relational evaluations of authorities (who represent the superordinate group and tend to be members of the dominant group) over instrumental evaluations of outcomes (Huo et al., 1996; Smith & Tyler, 1996). Interestingly, although a dual identity manipulation (making both a common ingroup identity and a subgroup identity salient) does not appear to undermine support for change (Ufkes et al., 2016), strong identification with both the superordinate group and a subgroup does appear to promote relational evaluations of authorities (Huo et al., 1996).

These lines of research suggest that prejudice reduction strategies have the potential to help perpetuate more subtle or structural forms of inequality (Dovidio et al., 2016). Dixon et al. (2012) argue that “it is precisely *because* contact improves intergroup attitudes (prejudice reduction) that it also decreases perceptions of discrimination, support for race-targeted policies, and readiness to engage in collective action” (p. 421). Indeed, Saguy et al. (2009) provide evidence that attitudes toward the (dominant) outgroup form part of the mechanism by which contact reduces support for social change. In other words, “harmonious relations” between dominant and subordinate groups might, in themselves, be “implicated in the reproduction of injustice” (Dixon, Tropp, Durrheim, & Tredoux, 2010, p. 79).

However, a recent meta-analysis suggests that the paradoxical effects of intergroup contact might be small and might depend on the outcomes measured and the type of contact (Reimer & Sengupta, 2020). Similarly, Reimer et al. (2020) found that, at least among one set of participants (Indian college students), intergroup contact and social identity inclusivity (with exclusivity measured through “us” versus “not us” judgments of individuals with whom participants share caste, religious, or national group membership) were unrelated to support for a form of affirmative action in higher education (though the authors suggested that the lack of effect might be due to participants having personally experienced the effects of the affirmative action policy in question). It would be valuable, then, to attempt to replicate paradoxical effects, especially of common ingroup identity, which has not been examined as thoroughly as intergroup contact.

If common ingroup identity has these paradoxical effects, an additional question is whether the type of common ingroup matters. Do these effects occur when the dominant group is not involved? It is plausible that a common ingroup identity that does not include the dominant group would not have the same paradoxical effects as a common ingroup identity that includes the dominant group because a common minority ingroup identity preserves the distinction between the ingroup and the dominant group. Furthermore, one study of intergroup contact found that higher quality contact between members of different subordinate groups could in fact increase support for policies and collective action that benefit the other group (Dixon et al., 2015). And there is some evidence that identification as POC, in particular, is associated with support for the Black Lives Matter movement among Black, Latino, and Asian Americans (Pérez, 2020). It is thus possible that a common minority ingroup identity could increase support for social change that benefits other minority groups.

Thus, the CIIM and the paradoxical effects literature suggest the following hypotheses:

Hypothesis 1: A common ingroup identity that includes the dominant group (American identity) predicts more positive attitudes toward other racial minority groups (and Whites).

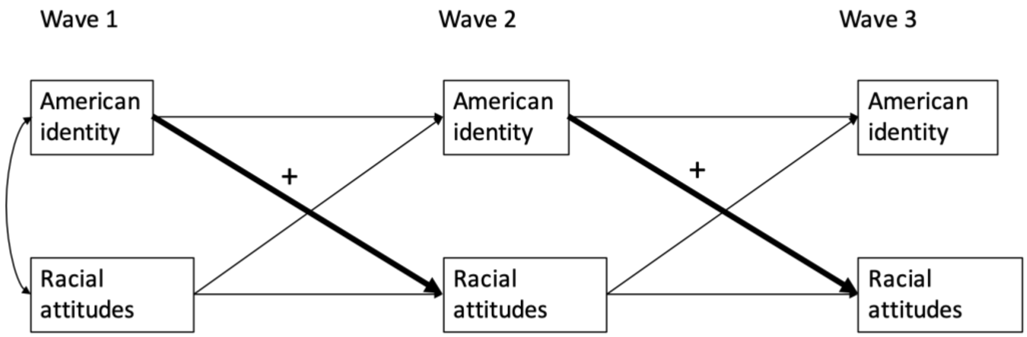
Hypothesis 2: A common ingroup identity that does not include the dominant group (person of color, or POC, identity) predicts more positive attitudes toward other racial minority groups.

See Figure 1 for an illustration of each of these hypotheses in a 3-wave panel model in which identity at an earlier time point predicts racial attitude at a later time point, controlling for racial attitude at the earlier time point, and racial attitude at an earlier time point predicts identity at a later time point, controlling for identity at the earlier time point. The hypothesized effect (identity predicting more positive racial attitudes) is shown in bold.

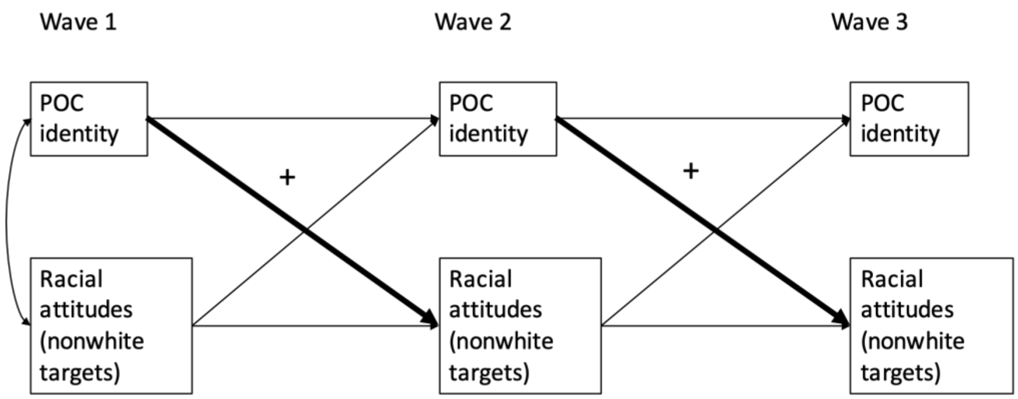
Hypothesis 3: A common ingroup identity that includes the dominant group (American identity) predicts less support for change.

Hypothesis 4: A common ingroup identity that does not include the dominant group (POC identity) predicts more support for change, especially change that benefits other minority groups.

See Figure 2 for an illustration of these hypotheses in a 3-wave panel model (with the hypothesized effects shown in bold as in Figure 1). Although the hypothesized effect for POC identity on support for change is again positive, the hypothesized effect for American identity is negative, as suggested by the paradoxical effects literature.

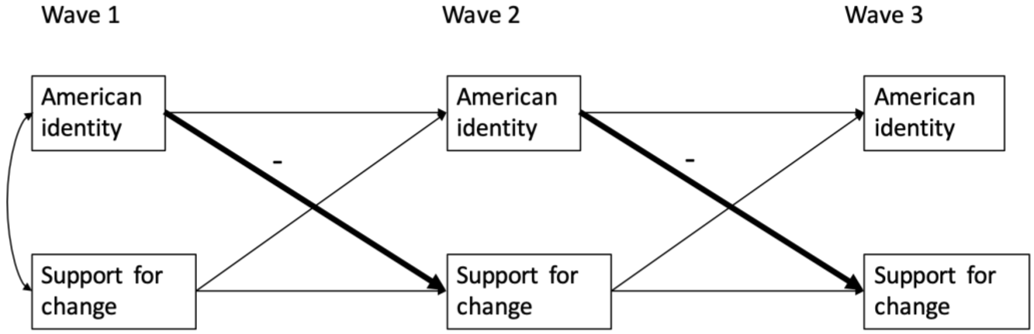


a.

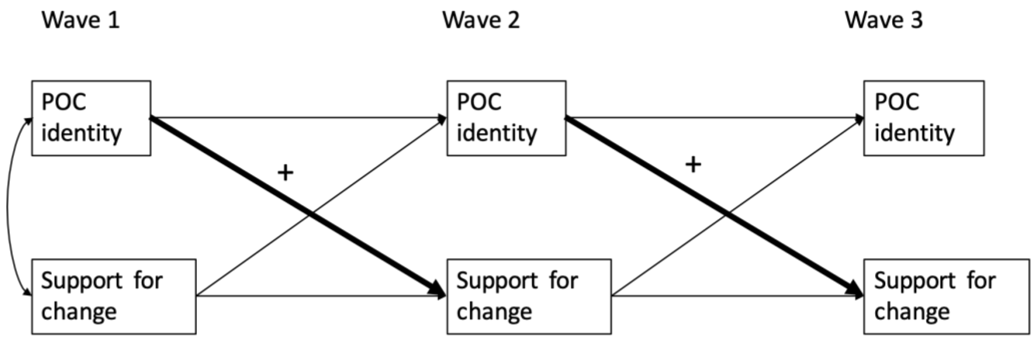


b.

Figure 1. Illustration of Hypothesis 1 (a) and Hypothesis 2 (b) in a 3-wave panel study. Hypothesized paths are in bold. Cross-lagged paths from both POC and American identity to racial attitudes are expected to be positive.



a.



b.

Figure 2. Illustration of Hypothesis 3 (a) and Hypothesis 4 (b) in a 3-wave panel study. Hypothesized paths are in bold. Cross-lagged paths from POC identity to support for change are expected to be positive. Cross-lagged paths from American identity to support for change are expected to be negative.

B. Collective Action Theory: How Racial Identity and Person of Color Identity Might Increase Support for Change

Although the paradoxical effects literature shows how prejudice reduction interventions can reduce support for social change, it does not explain how support for social change arises in the first place. Dixon et al. (2010b) refer to the collective action approach (Wright & Lubensky, 2008) as an alternative to the prejudice reduction approach that focuses on motivating members of disadvantaged groups to challenge the status quo.

1. Social Identity Theory and Predicting Collective Action

Collective action theory is heavily influenced by social identity theory (see, e.g., Wright, 2010). But whereas the SIT-based concepts of intergroup comparison and competition are treated as sources of prejudice in the prejudice reduction literature, Tajfel and Turner's (1979) formulation of SIT conceptualized social competition as a key process by which members of low-status groups can achieve a more positive social identity. In contrast to prejudice reduction's tendency to focus on dominant group members, SIT "focuses in particular on what happens when a given social identity confers negative self-description and/or low social status on an individual" (Oakes, 2002, p. 813). Tajfel and Turner (1979) proposed three categories of reactions that members of low-status groups can use to buffer their self-esteem: individual mobility, social creativity, and social competition. Individual mobility involves attempts to dissociate from the low-status group and become part of a higher-status group; social creativity involves redefining the intergroup situation by changing the dimension of comparison, the values of different attributes on the comparison dimension, or the relevant comparison group; social competition involves directly competing with the dominant group to attempt to change the status quo (Tajfel & Turner, 1979). Thus, social competition can lead to intergroup conflict if the relevant comparison dimension involves scarce resources; individual mobility and social creativity can reduce intergroup conflict but leave the group's objective disadvantages intact (Tajfel & Turner, 1979). Whether individuals choose social competition depends on their identification with the subordinate group and their perception of the dominant group as a relevant outgroup for social comparisons (Tajfel & Turner, 1979).

In keeping with these ideas from SIT, then, Dixon et al.'s (2012) argument that prejudice reduction strategies undermine exactly the processes that drive subordinate group members' support for social change seems especially plausible when applied to the CIIM. By de-emphasizing the basis for social comparison with the dominant group, common ingroup identity might suppress intergroup competition processes that underlie both prejudice and social change. However, this effect should only occur if the dominant group is no longer perceived as a relevant comparison outgroup (i.e., if the dominant group is part of the common ingroup). Focusing on the social identity mechanisms behind collective action leads to the possibility that a common ingroup identity that does not include the dominant group could instead increase social change motivations by increasing the relevance of comparison with the dominant group.

In the SIT framework, collective action is defined as a form of social competition (Wright, 2010). Thus, SIT-based theories of collective action begin with the conditions that predict choosing individual mobility, social creativity, and social competition as identity management strategies. These include subjective identification with the ingroup, as well as the perceived existence and strength of barriers to leaving the low-status group, security of status differences (i.e., availability of cognitive alternatives to the current status differences), and legitimacy of the status differences (Tajfel & Turner, 1979). The perceived societal conditions are also referred to as the socio-structural variables of perceived permeability of group boundaries, perceived stability of the status quo, and perceived legitimacy of the status quo (Wright, 2010).

Subjective identification with the ingroup is further defined by self-categorization theory (SCT). According to Hogg and Turner (1987) identification occurs when individuals "define, describe, and evaluate themselves in terms of the group/category label," and self-categorization is the cognitive process through which identification occurs (p. 325). Self-categorization as a group member thus transforms behavior into group behavior (Hogg & Turner, 1987), or rather, moves behavior along the continuum from more individual to more group-like (Turner & Reynolds, 2012). Group behavior (or intergroup behavior) involves the individual perceiving the self and others as members of different groups and acting as a representative of the ingroup; collective action is a form of group behavior aimed at maintaining or improving the ingroup's position (Wright, 2010). SCT also addresses when and how self-categorization occurs through the concepts of accessibility and normative and comparative fit (Turner & Reynolds, 2012).

Because people are motivated to achieve a "positively valued social identity" (Ellemers et al., 1988, p. 498), members of low-status groups are motivated to engage in various forms of identity enhancement strategies (e.g., Ellemers et al., 1993), including both individual mobility and social mobility (Wright, 2010), social creativity (Mummendey et al., 1996), and social competition (Haslam & Reicher, 2006). The socio-structural variables are theorized to predict choices among these strategies and to both influence and be influenced by group identification (Wright, 2010). Permeability of group boundaries has been found to predict lower identification with the disadvantaged group (Ellemers, et al., 1988) and greater preference for individual mobility strategies (Wright et al., 1990). Illegitimate group status differences predict higher group identification among members of low-status groups, especially when group status is unstable and group boundaries are impermeable (Ellemers, Wilke, & van Knippenberg, 1993).

2. Incorporating Relative Deprivation into Collective Action Theory

But some evidence suggests that the SIT socio-structural variables might better predict when people choose individual or social mobility strategies, while variables derived from relative deprivation theory (RDT) might better predict when people choose social competition strategies (Mummendey, Kessler, Klink, & Mielke, 1999). Using structural equation models that included variables from both theories, Mummendey et al. (1999) found that the SIT variables stability, legitimacy, and permeability predicted in-group identification, which in turn directly predicted East Germans' endorsement of mobility and recategorization in the face of their group's lower status compared to West Germans; they found that the RD variable of fraternal resentment directly predicted, and mediated the effects of the SIT variables and in-group identification on, endorsement of social and realistic competition. Thus, some sense of group-based deprivation seems to be important in predicting when members of low-status groups attempt to improve their group's relative status. Indeed, Tajfel and Turner (1979) intended SIT to complement other theories, such as realistic conflict theory, in explaining intergroup relations in the real world.

It is also unclear whether group identification mediates the relationships between perceived permeability, legitimacy, and stability and collective action (Mummendey, Klink, et al., 1999) or if the socio-structural variables should mediate the relationship between ingroup identification and collective action.

To organize the SIT and RDT predictors of collective action, van Zomeren et al. (2008) proposed the social identity model of collective action (SIMCA). Under SIMCA, identity predicts collective action both directly and indirectly via injustice and efficacy (van Zomeren et al., 2008; see also van Zomeren, Leach, & Spears, 2012). Injustice includes both perceptions of unfairness or discrimination and affective reactions (e.g., group-based anger), though affective injustice is a stronger predictor of collective action (van Zomeren et al., 2008). However, van Zomeren et al. (2008) found that injustice and efficacy more strongly predict collective action against what they call incidental disadvantages (issue- or situation-specific disadvantages, such as a tax or tuition increase) than collective action against structural disadvantages (e.g., long-standing racial hierarchies). Identity predicts collective action against both types of disadvantage, but it tends to do so directly with regard to structural disadvantage (van Zomeren et al., 2008). Van Zomeren et al. (2008) further distinguish between politicized identities (e.g., identification with a social movement) and non-politicized identities (i.e., identification with the group as a whole), with the former more strongly predicting collective action than the latter (see also Klandermans, 2014).

Using a theoretical framework from the literature on coping, van Zomeren et al. (2012) re-conceptualized SIMCA as a dual-process model of emotion-focused and problem-focused coping with collective disadvantage. Identity shapes a primary appraisal of whether the collective disadvantage is self-relevant (i.e., relevant to the individual's personal or group-based self-concept) (van Zomeren et al., 2012). For the disadvantage to be perceived as relevant to the group-based self-concept, the individual must self-categorize as a group member (van Zomeren et al., 2012). Injustice and efficacy relate to secondary appraisals of blame and coping potential, which drive emotion-focused and problem-focused coping, respectively (van Zomeren et al., 2012). The primary appraisal of group-based self-relevance increases secondary appraisals of both blame and coping potential, and both secondary appraisal pathways can lead to collective action as a form of approach coping (van Zomeren et al., 2012).

The original SIMCA and the dual-pathway coping model differ in a few respects. First, although group identification predicts group-based anger and (maybe) efficacy in both models, group identification in the dual-pathway model also moderates the effect of group efficacy beliefs on collective action, with efficacy having a stronger effect for low identifiers (van Zomeren et al., 2012). Second, engaging in collective action can strengthen the primary and secondary appraisals in a feedback loop; thus, in the dual-pathway model, collective action can both be predicted by and predict group identification. Third, where SIMCA suggests that the emotion of anger is central to the injustice path, the dual-pathway model also draws attention to the judgments that the situation is unfair and that an external agent is to blame for it, which drive group-based anger (van Zomeren et al., 2012); this suggests that measures of both anger and assessments of unfair disadvantage might be relevant. Finally, the original SIMCA includes a direct effect of identity on collective action, especially with regard to structural disadvantage (van Zomeren et al., 2008); in the dual-pathway model, the effect appears to be completely mediated by injustice and efficacy (van Zomeren et al., 2012).

3. Collective Action Theory and Mechanisms for Paradoxical Effects

Elements of SIMCA in both its original form and its dual-pathway form can be found in the research on the paradoxical effects of prejudice reduction. Ufkes et al.

(2016) found that group-based anger and group efficacy beliefs mediated the sedative effect of a common ingroup manipulation on collective action intentions and that the effect of the common ingroup manipulation on these two mediators was mediated by beliefs about whether racial inequality exists. (However, because dual identity did not have the same sedative effect, these findings could primarily be a product of the common ingroup manipulation reducing subgroup identification.) Belief that racial inequality exists could logically be part of the primary self-relevance appraisal (i.e., whether some disadvantage the individual is currently experiencing has to do with their racial group membership) or part of the secondary blame appraisal (i.e., whether there is an unfair racial hierarchy that is not the ingroup's fault) from van Zomeren et al.'s (2012) dual pathway model. Ufkes, Dovidio, and Tel (2015) similarly found that subgroup identification (Kurdish) predicted higher collective action intentions via anger and efficacy but that superordinate group identification (European) predicted lower collective action intentions with regard to structural disadvantage via decreased anger. Combining theories of intergroup contact and collective action, Cakal et al. (2011) tested relative deprivation (operationalized as recognition of the ingroup's disadvantage compared to the outgroup) and group efficacy as mediators of the effects of disadvantaged group identity and intergroup contact on collective action and policy support, finding significant indirect effects of contact through both mediators but of disadvantaged group identity only through group efficacy. This collection of studies provide evidence that disadvantaged subgroup identification can increase support for change via both the anger/perceived disadvantage and efficacy pathways and that superordinate group identification can decrease support for change at least via the anger/perceived disadvantage pathway.

Other studies of intergroup contact appear to have focused primarily on the injustice pathway. Saguy et al. (2009) found that positive contact with Jewish Israelis predicted decreased support from Arab Israelis for legislation and general social change to improve their relative position and that this effect was partially mediated by perceptions of the existing inequality as just. Tropp et al. (2012) found, in a longitudinal study, that friendships with Whites predicted lower perceived ethnic discrimination among Black and Latino college students, which in turn predicted less support for ethnic activism among Black students (and marginally predicted less support for ethnic activism among Latino students). A more recent study of college students found similar effects of friendships with Whites among both minority and White students (Carter et al., 2019). These findings and the fact that Carter et al. (2019) refer to their perceived discrimination variable as "perceived injustice" suggest that perceived discrimination might reflect a similar construct to injustice appraisals or relative deprivation. Together, these studies demonstrate that 1) collective action theory can help explain the paradoxical effects of prejudice reduction by suggesting relative deprivation and group efficacy as mediators and 2) variables related to relative deprivation and group efficacy potentially mediate the effects of group identification on policy support as well as collective action (but see Tausch et al., 2011, Study 2, for an example in which perceived group disadvantage but not anger or efficacy predicted policy support).

Additionally, Saguy et al. (2009) found that attitudes toward the dominant outgroup partially mediated contact effects via perceived outgroup fairness, thus directly connecting the prejudice reduction and sedative effects of intergroup contact. The perceived outgroup fairness effect, in turn, could relate to research suggesting that hope for harmony (Hasan-Aslih et al., 2019) or belief that injustices will be addressed anyway (Stroebe, 2013) can undermine collective action outside of the injustice and efficacy pathways. It is also consistent with Mummendey, Klink, et al.'s (1999) finding that in some contexts (i.e., when the group's status is expected to improve under the current regime) perceived stability of the status quo (i.e., lack of improvement) is positively associated with social competition strategies instead of negatively associated, as SIT would predict in most situations. What perceived outgroup fairness and Mummendey, Klink, et al.'s (1999) reversal of the stability effect might be capturing is the idea that if the dominant outgroup is perceived as being likely to improve the subordinate group's status, subordinate group members might view collective action or political action as unnecessary or even counterproductive (i.e., by upsetting the dominant group). The role of perceived outgroup fairness also brings to mind findings from the group-value model of justice literature that superordinate group identification increases the role of relational evaluations (i.e., whether the authority treated them respectfully) over instrumental evaluations (i.e., evaluations of outcomes) in the feeling of obligation to obey the law (Smith & Tyler, 1996). All of these examples seem to involve a recognition that the group is unjustly disadvantaged, paired with a belief that dominant group authorities either already are fair (even if they produce unfair outcomes) or will become fairer in the future; thus, they could reflect boundary conditions on the injustice pathway.

In summary, SIMCA predicts that identification with a disadvantaged subgroup should be associated with increased support for collective action and potentially other forms of social change that benefit the group, and this effect should be mediated by increased perceptions of group-based injustice and group efficacy. The paradoxical effects studies incorporating SIMCA suggest that identification with a common ingroup that includes the dominant group should decrease support for change via at least the perceived injustice pathway. (As discussed above, there is less evidence for an efficacy pathway for paradoxical effects.[3])

However, by these same mechanisms, a common ingroup identity that does not include the dominant group might increase support for social change. Instead of decreasing perceived injustice and efficacy, a common minority ingroup identity could increase group efficacy (for example, because it is a larger group with more visibility or voting power) and/or recognition of unjust disadvantages compared to the dominant group (by making the dominant group a more relevant or salient comparison group). Indeed, Dovidio, Gaertner, and Saguy (2009) note that recategorization can increase bias toward outgroups that were not included in the common ingroup, which suggests that recategorization made comparisons with those outgroups more relevant. If the same social identity mechanisms indeed underlie prejudice and social competition, a common minority ingroup identity could make comparisons with Whites more relevant and thus lead to more negative attitudes toward Whites and increased social competition to address inequality with Whites.

Additionally, building on the dual-pathway model (van Zomeren et al., 2012), if the collective disadvantage in question affects a minority outgroup rather than one's own group, identification with a common minority ingroup should increase the appraised self-

[3] Indeed, when the common ingroup identity is "American," it is possible that identification with this group could be associated with *greater* efficacy, to the extent that being American is associated with citizenship (e.g., among heavily immigrant groups such as Latino and Asian Americans) or civic engagement.

relevance of that disadvantage (because it affects the common ingroup), and this primary appraisal should feed secondary appraisals of injustice and group efficacy, thus increasing support for change. This suggests that the effects of POC identity should be strongest for policies that are perceived as primarily affecting minority groups other than one's own.

Restated, these observations form the following hypotheses:

Hypothesis 5: For racial minorities, racial identity predicts more support for change, mediated by increases in perceived unjust racial disadvantage (e.g., perceived racial discrimination) and perceived racial group efficacy.

Hypothesis 6: For racial minorities, POC identity predicts more support for change, mediated by increases in perceived unjust racial disadvantage (of POC generally) and perceived POC efficacy. These effects should be strongest for policies that primarily affect other minority groups.

Hypothesis 7: For racial minorities, American identity predicts less support for change, mediated by decreases in perceived unjust racial disadvantage (of one's own group and POC generally). Because evidence for an efficacy pathway in the existing literature is weaker, I did not predict that efficacy would mediate the effect of American identity.

C. Group Consciousness as a Pathway to Support for Change

Political psychologists have also examined the effects of group membership on political behavior. But much of the political behavior research has done so without delving into the process behind this link (Lee, T., 2008). To the extent that explanations were sought for group differences, theorists tended to turn to resource availability (Miller et al., 1981). Nonetheless, subjective identification explanations have been developed for when group membership translates into political attitudes and behavior (e.g., Conover, 1984; Miller et al., 1981).

This literature on group identity and political behavior suggests different sets of mechanisms for the identity-behavior relationship from those proposed by social psychologists studying collective action. Social identity theory has been less influential in political science than it has been in psychology, perhaps in part because it has been perceived as less relevant to political behavior in the real world (Huddy, 2001) and in part because SIT was relatively new (see Tajfel & Turner, 1979) and SCT had not been established (see Turner et al., 1987) when identity theories of politics were being developed (e.g., Gurin, Miller, & Gurin, 1980; Conover, 1984). Conover's (1984) concept of self-schemas resembles self-categorization except that self-schemas appear to be more stable, and thus, a political psychology of group identification could have resembled collective action theory. However, although Conover (1984) found that subjective group identification could predict issue positions consistently with a self-schema account, other political behavior researchers were interested in predicting political participation, which group identification predicted less well. To predict participation, some political science and public opinion researchers turned to Marx's concept of class consciousness to develop a theory of group consciousness (Gurin, Miller, & Gurin, 1980).

1. Group Consciousness Theory

According to Gurin et al. (1980), consciousness is distinct from identification because identification consists of awareness of similarity to other group members while “[c]onsciousness refers to a set of political beliefs and action orientations arising out of this awareness of similarity” (p. 30), specifically beliefs and action orientations related to the group’s position in society compared to other groups. Transformation of identification into consciousness is proposed as the process connecting identity to political behavior (Miller et al., 1981), which implicitly suggests that consciousness could be a mediator between identification and political behavior. By emphasizing the role of conflict and structural factors in this transformation, Gurin et al. (1980) distinguished their theory from social identity theory and tied it more to realistic conflict theory and relative deprivation theory.

In its original form, group consciousness consisted of four hypothesized dimensions: identification, power discontent (i.e., the sense that one’s group has too little influence in society), rejection of the legitimacy of group status differentials (i.e., blaming the system for these differentials), and collectivist orientation (i.e., belief that people should use collective action over individual action to pursue the group’s interests) (Gurin et al., 1980). Another version omits collectivist orientation, replaces power discontent with polar power (which includes both feeling that one’s own group has too little influence and feeling that an outgroup has too much influence), and adds polar affect (i.e., differential affect for the ingroup and outgroup) (Miller et al., 1981). Miller et al. (1981) also define identification in a way that emphasizes shared interests with the ingroup rather than general similarity. And they found that the interaction among identification, polar power, and system blame predicted turnout in Presidential elections (Miller et al., 1981).

In addition to predicting political behavior, group consciousness is relevant to a theory of group identity and support for change because it potentially overlaps with variables from collective action theory and is affected by intra- and intergroup contact. Indeed, one might expect overlap between group consciousness and the relative deprivation elements of collective action theory because group consciousness theory was partially influenced by relative deprivation theory (see Gurin et al., 1980). Polar power and system blame, on their face, resemble unfairness and blame appraisals, respectively, from van Zomeren et al.'s (2012) dual-pathway model. Polar power has also been referred to as deprivation (Lien, 1994), further suggesting overlap with the relative deprivation concepts that became the injustice pathway in SIMCA. System blame has been operationalized as perceived discrimination or awareness of discrimination against the ingroup or against oneself as a member of the group (Lien, 1994; Rodriguez & Gurin, 1990), potentially connecting the group consciousness literature to Tropp et al.'s (2012) intergroup contact study. Furthermore, Rodriguez and Gurin (1990) found that while ingroup contact predicts power discontent, perceived illegitimacy of subordination (i.e., system blame), and support for group-based political action among Mexican Americans, contact with Whites predicts lower perceived illegitimacy of subordination. This finding suggests that the system blame element of group consciousness could partially explain the paradoxical effects of contact, consistent with Tropp et al.'s (2012) findings. Additionally, contact with members of other minority groups (other Latinos, Blacks, Asians, and Native Americans) predicted higher perceived illegitimacy of subordination and support for group-based political action (Rodriguez & Gurin, 1990), suggesting a possible mechanism (through awareness of discrimination) by which POC identity might increase support for change.

System blame also brings to mind the social psychological concept of system justification (i.e., the motivation to justify or bolster the status quo), which has been proposed as an additional (negative) predictor of collective action (Jost et al., 2017). One way in which system justification has been operationalized is as endorsement of status-legitimizing ideologies, i.e., widespread beliefs within a culture that justify inequalities between groups (Major et al., 2002; Sengupta & Sibley, 2013). Relatedly, social dominance theory predicts that endorsement of hierarchy-enhancing versus hierarchy-attenuating legitimizing ideologies justify support for policies that increase or decrease intergroup inequality, respectively (Levin et al., 1998). Major et al. (2002) found that low-status group members who endorsed one such status-legitimizing or hierarchy-enhancing legitimizing ideology (potential for individual mobility) were less likely to attribute rejection by a higher-status group member to discrimination. Attribution to discrimination itself resembles system blame, though what is being attributed in Major et al.'s (2002) studies is a negative personal outcome rather than a group's position in society.

Furthermore, although Jost et al. (2017) seem to suggest that system justification affects collective action independently of group identification, Jost et al. (2003) proposed that identity salience should predict (lower) system justification among members of low-status groups. Levin et al. (1998) similarly predicted that group identification should be negatively associated with endorsement of hierarchy-enhancing legitimizing myths among members of low-status groups. Consistent with these predictions, Major et al.

(2002) found that low-status group members' group identification and belief in individual mobility tended to be negatively correlated. Levin et al. (1998) similarly found a negative association between racial or ethnic group identification and endorsement of a number of hierarchy-enhancing legitimizing myths, including individual mobility, legitimacy of racial inequality, and internal attributions for racial differences in poverty, for African Americans and Latinos (but not Asian Americans). Identification with a superordinate group, on the other hand, has been found to predict increased system justification among disadvantaged group members (Jaśko & Kossowska, 2013). And support for meritocracy, another system-justifying ideology, has been shown to mediate the relationship between positive intergroup contact and reduced support for policies that benefit the disadvantaged ingroup (Sengupta & Sibley, 2013). Taken together, these findings suggest that system justification and/or endorsement of legitimizing ideologies might mediate the relationship between subgroup and/or superordinate group identification and support for change.

It is unclear, however, whether this phenomenon comprises part of relative deprivation or group consciousness or whether it independently predicts some part of the collective action or political behavior pathways. For example, Jaśko and Kossowska (2013) conceptualize system justification as a measure of perceived fairness or legitimacy, which suggests connections to perceived legitimacy in SIT, van Zomeren et al.'s (2012) appraisals of unfairness and blame, or a combination of the system blame and power discontent variables from group consciousness theory. And Levin et al.'s (1998) hierarchy-enhancing and hierarchy-attenuating legitimizing myths include SIT-related beliefs about legitimacy and permeability, as well as inequality attributions and perceived discrimination, which overlap with the system blame facet of group consciousness.

2. Linked Fate

In addition to the Gurin et al. (1980) and Miller et al. (1981) dimensions of group consciousness, some group consciousness measures include or even consist of a measure of linked fate with the ingroup (Sanchez & Vargas, 2016). However, linked fate was initially distinct from group consciousness (Dawson, 1994). Dawson (1994) describes linked fate as part of the “black utility heuristic,” which explains African Americans’ relatively uniform political behavior as a product of using racial group interests to determine individual interests when making political choices. Linked fate measures “the degree to which African Americans believe that their own self-interests are linked to the interests of the race” (p. 77), typically using two branching items, such as “Do you think what happens generally to [group] people in this country will have something to do with what happens in your life?” (Dawson, 1994, p. 77) and if yes, “Will it affect you a lot, some, or not very much?” (Sanchez & Vargas, 2016). Linked fate and “black economic subordination” (whether the individual perceives the economic position of Blacks as better than, worse than, or the same as Whites’) jointly predicted African Americans’ economic and racial policy preferences (Dawson, 1994).

Despite Dawson’s (1994) emphasis on the self-interest definition of linked fate, he describes it as partly a product of self-categorization as a group member. Furthermore, the concept of linked fate recalls Conover’s (1984) idea that group identification and development of a group-based self-schema connects group interests to the self, whether as a proxy for self-interest or through solidarity with the group that makes its interests directly relevant to the self. Conover (1984) argued that the direct self-relevance of group interests was a more likely explanation. Thus, linked fate, which captures the perception of group interests as self-relevant, could be a mechanism connecting group identity and group-oriented policy preferences. Unlike the aspects of group consciousness that overlap with the collective action and paradoxical effects literature, however, linked fate does not have an immediately apparent connection to superordinate identities that include the dominant group (i.e., American identity). It is possible that identification as American might reduce linked fate with one's racial group or with POC, but the definition and operationalization of linked fate suggest that racial and POC linked fate are more directly connected to racial and POC identities, respectively, and that American identity need not reduce linked fate unless it also reduces subgroup identification.

3. Disentangling Identification, Linked Fate, and Group Consciousness

Although linked fate was developed to explain African Americans' political behavior, it has been measured in Asian and Latino Americans as well (e.g., Junn & Masuoka, 2008; Lien, Conway, & Wong, 2004; Sanchez & Masuoka, 2010). Similarly, studies of Asian and Latino Americans have used some form of group consciousness measures (e.g., Lien, 1994; Rodriguez & Gurin, 1990). But the concepts of linked fate and group consciousness for different racial and ethnic groups have generally not been clearly delineated (see, e.g., Lee, T., 2008). Indeed, it is unclear which dimensions of group consciousness define that concept in general: Are identification, collectivist orientation, and polar affect part of the concept, or are they antecedents, consequences, or related concepts? Lien (1994) seems to suggest that identification is distinct from the more political concepts of polar power and system blame. Operationalizing identification as perceiving that there are problems of special concern to ingroup members (which seems conceptually similar to linked fate) and system blame as perceived prejudice and discrimination, Lien (1994) found identification, system blame (renamed alienation) and polar power (renamed deprivation) to be distinct from each other for Mexican and Asian Americans. Sanchez and Vargas (2016) examined the factor structure of group commonality (i.e., similarity to ingroup and ingroup members), perceived discrimination against the ingroup, collective action orientation, and linked fate for White, Black, Hispanic, and Asian Americans. They found that a single factor dominated by perceived discrimination (followed by linked fate) adequately captured this concept for African Americans but that two factors were needed for Asian and Latino Americans (Sanchez & Vargas, 2016). For both Latino and Asian Americans, linked fate and perceived discrimination load on separate factors, with commonality loading on the same factor as linked fate and collective action orientation loading on the same factor as perceived discrimination (Sanchez & Vargas, 2016, Table 3).

Linked fate has been found to predict more support for the Black Lives Matter movement (Merseth, 2018) and greater perceived political commonality with African Americans (Nicholson, Carter, & Restar, 2020) and Latinos (Lu, 2020) among Asian Americans. It has also been found to predict lower endorsement of negative Black stereotypes and greater perceived commonality with Blacks over Whites among Latino Americans (McClain et al., 2006). For Asian Americans, perceived commonality with Blacks and Latinos, in turn, has been found to predict support for a path to citizenship for undocumented immigrants (Samson, 2015) and alignment with the Democratic Party (Kuo, Malhotra, & Mo, 2014). Findings on the effects of aspects of group consciousness among Latino and Asian Americans, on the other hand, are mixed at best. One study found that aspects of Latino group consciousness (commonality with other Latino groups and perceived discrimination against Latinos) appear to predict perceived commonality with African Americans (Sanchez, 2008), but another study found no such effect of perceived discrimination (Kaufmann, 2003), and a third found that experiences of discrimination did not predict perceived commonality with Blacks among native-born Latinos but predicted less perceived commonality with both Blacks and Whites among foreign-born Latinos (Wilkinson, 2014). Alienation (i.e., perceived prejudice and discrimination) appears to predict political behavior besides voting for Latinos but not for Asians (Lien, 1994). For Asian Americans, there is evidence that perceived cultural, racial, economic, and political commonality with other Asian Americans predicts perceived commonality with African Americans, but perceived discrimination does not (Nicholson et al., 2020). The effects of perceived discrimination on perceived commonality with Latinos appears mixed (Lu, 2020). Although perceived discrimination against Asian Americans was correlated with support for Black Lives Matter in Merseth's (2018) study, this relationship became non-significant once identity importance, linked fate, and perceived anti-Black discrimination were controlled for.[4] But Kuo et al. (2014) found evidence that experiences of discrimination predict Asian Americans' identification with the Democratic Party over the Republican Party.

[4] Racial identity importance was also positively correlated with support for Black Lives Matter in Merseth's (2018) study, but this relationship also became non-significant in the multiple regression model. One possible explanation for this observation is that linked fate might mediate the effect of identity importance.

Based on the Sanchez and Vargas (2016) factor structure and the findings of what linked fate and perceived discrimination predict among Latino and Asian Americans, I would expect linked fate and possibly perceived discrimination to connect a more psychological form of racial or ethnic identification with Asian and Latino Americans' political attitudes. (For African Americans, these two variables might reflect the same underlying concept.) Rodriguez and Gurin's (1990) findings further suggest that a perceived discrimination factor of group consciousness could mediate the effects of common ingroup identity and common minority ingroup identity on political attitudes.

On the other hand, as discussed above, the literature on linked fate does not appear to connect it to American identity (i.e., there is no evidence that identifying as American, by itself, decreases the sense of linked fate with one's racial or ethnic group). Thus, to the extent that identification as American is independent of racial or POC identification, I would not expect linked fate to mediate the effects of American identity on political attitudes.

Because group consciousness is theoretically group-specific, I would expect versions of these variables pertaining to the racial group and people of color to be distinct mediators. However, Rodriguez and Gurin's (1990) finding that intra-minority group contact predicted higher perceived discrimination against people of Mexican descent (they did not have a measure perceived discrimination against racial minorities as a whole) suggests that measures of perceived discrimination against the racial group and against POC might capture the same concept. Among Asian Americans, group consciousness and linked fate might cut across levels of group identity: Asian American identity was found to relate to perceived commonality with Blacks and Latinos (Cho, 2020); linked fate and group consciousness at the racial group level have been found to predict perceived commonality with African Americans (Nicholson et al., 2020); and linked fate with both Asian Americans and other racial minorities has been found to predict support for Black Lives Matter (Merseth, 2018). Thus, while the original theory suggests unique pathways for racial and POC versions of linked fate and perceived discrimination between identity and political attitudes, the racial and POC measures might empirically form a single linked fate pathway and a single perceived discrimination pathway.

Hypothesis 8: Racial identity predicts more support for change, mediated by increased linked fate with the racial group and increased perceived discrimination.

Hypothesis 9: POC identity predicts more support for change, mediated by increased linked fate with people of color and increased perceived discrimination.

Hypothesis 10: American identity predicts less support for change, mediated by decreased perceived discrimination. I did not predict that linked fate would mediate the effect of American identity.

D. Identity and Perceived Discrimination/Inequality: What are we measuring?

1. Identity

Collective action theory, group consciousness theory, and some of the paradoxical effects literature all address the relationship between identity and support for social change. But to what extent do these areas of research mean the same thing by “identity”?

a. Identity manipulations, identity measures, and identity salience. Both the minimal group paradigm and the CIIM were developed and initially tested with experiments that created new groups in the lab (e.g., Tajfel et al., 1971; Gaertner et al., 1989). Manipulating identity in these studies thus involves manipulating 1) the existence of particular groups and 2) assignment of participants to these lab-created groups. However, group assignment is not sufficient to produce intergroup behavior (Oakes, 2002); as Tajfel and Turner (1979) emphasized, subjective identification with the group is necessary to observe these effects (but see Hong & Ratner, 2020, for an example of categorization effects that do not depend on subjective identification in some versions of the minimal group paradigm). And identities created in the lab may not inspire the same level of subjective identification as many real-world groups. Thus, lab-created superordinate identities can be unstable over time and can sometimes be perceived as an identity threat, leading to increased bias in favor of the original ingroup rather than identification with the superordinate group (Dovidio et al., 2009). To have the intended effects, then, identity manipulations need to prime participants to subjectively identify with their assigned group in the context in which attitudes or behaviors will be studied.

More recent descriptions of the CIIM start from the idea of social categorization (of self and others) and the fact that people can have multiple group identities at different levels of inclusiveness that are available to them in a given situation (e.g., Dovidio et al., 2009). These levels of identity presumably include both lab-created identities and existing real-world identities. Categorization into a particular level depends on one’s past experiences and one’s goals and expectations in the current situation (Dovidio et al., 2009). Accordingly, some studies involving the CIIM have primed the salience of existing identities (e.g., Górska & Bilewicz, 2015; Ufkes et al., 2016; White, Schmitt, & Langer, 2006, Study 3) or primed a shared experience with another group, presumably to make a shared superordinate identity salient (Glasford & Calcagno, 2012; Craig &

Richeson, 2012). Priming experiences of discrimination can have different effects depending on whether the target group shares a dimension of disadvantage with participants' ingroup: Reminders of racial discrimination can reduce racial minorities' bias against other racial minority groups (Craig & Richeson, 2012), but reminders of sexism can increase White women's racial bias (Craig et al., 2012). These contrasting findings suggest that common ingroup identity might be easier to make salient when such an identity already exists (e.g., POC or racial minority) than when it is created by the salience manipulation (e.g., shared identity as people with a marginalized identity). Alternatively, existing common ingroup identities might pose less of an identity threat and consequently, trigger less resistance to identifying with them when primed (see Dovidio et al., 2009). Either way, CIIM studies that manipulate identity mostly seem to prime the salience of a social identity in the experimental context, but with rare exceptions (Ellemers, Spears, & Doosje, 1997), researchers have not attempted to manipulate the degree of identification with a group.

By contrast, much of the collective action and group consciousness literature involves correlational studies in which identity is measured (e.g., Kessler & Mummendey, 2002; Klandermans, 2014; Cakal et al., 2011; Rodriguez & Gurin, 1990; Junn & Masuoka, 2008). Similarly, research on the paradoxical effects of prejudice reduction tends to be correlational (Reimer & Sengupta, 2020), including measures of both intergroup contact (e.g., Tropp et al., 2012; Dixon et al., 2007) and identity (e.g., Ufkes et al., 2015; Jaśko & Kossowska, 2013). Highlighting the difference between measured identification and manipulated identity salience in political psychology, Huddy (2001) criticized SIT in part because situational salience often cannot explain when and how identity predicts political behavior. Furthermore, Transue (2007) demonstrated that an identity salience manipulation can have opposite effects on policy attitudes depending on whether the participant subjectively identifies with the group that is made salient through the manipulation.[5] But studying the CIIM in the same context as collective action and political behavior requires these two operationalizations of identity to be comparable.

Self-categorization theory and SIT/SCT-based collective action theories potentially connect measured and manipulated group identity via the process of self-categorization. Collective action on behalf of an ingroup depends on self-categorization as a member of that group (Wright, 2010). Self-categorization depends on the relative salience of different identities, which in turn depends on the interaction between the accessibility and fit of different categories in a particular context (Turner et al., 1994; Turner & Reynolds, 2012). Accessibility refers to the individual's readiness to use a particular self-category; fit refers to perceptions of intragroup similarities and intergroup differences that are consistent with the individual's expectations about the groups (normative fit) and perception of intergroup differences as larger than intragroup differences in the relevant context (comparative fit) (Turner et al., 1994). Thus, priming salience in the lab (via perceived fit in the experimental context) is one way to promote self-categorization into a particular group in a particular context (e.g., Hogg & Turner,

[5] Transue's (2007) identity salience manipulation differs from other identity salience manipulations, however, because the manipulation was the measure of group identification. More traditional identity salience manipulations either gave participants a group label or prompted them to think about themselves as members of a particular group, without giving them an obvious outlet to think about why they would *not* identify with the group. By giving participants a means to think about their non-identification, Transue's (2007) identity manipulation might have made salient *whether* the participant identified with the target group, rather than group identification per se.

1987). Having that identity chronically accessible (i.e., high readiness to use that self-category across contexts) because it is important or central to one's self concept might be another way to promote self-categorization in the same context (see, e.g., Jackson, 1999, citing Turner et al., 1987). Similarly, manipulating group involvement (Ellemers et al., 1997) might promote self-categorization through accessibility, as people who feel more involved with the group might show higher readiness to use that self-category across contexts. Van Zomeren and colleagues reach a similar conclusion, proposing that both situational salience and highly identified group members' chronic identity salience promote the self-categorization necessary to appraise collective disadvantage as self-relevant (van Zomeren et al., 2012). To the extent that self-categorization in a particular context is what matters for predicting support for change, then, priming identity salience and measuring chronic salience of that identity should produce similar results.

Additionally, because I measured identification rather than prompting respondents to identify with a group, resistance to recategorization (e.g., Dovidio et al., 2009; Crisp, Stone, & Hall, 2006) unlikely to pose a problem; after all, respondents could simply indicate that they do not identify with one or more groups. Furthermore, POC and American identities exist in the real world, and there is evidence that at least some racial minorities identify as American (e.g., Lien et al., 2003; Junn &Masuoka, 2008). There is also evidence that, for racial minorities, both American identity (Ufkes et al., 2016) and shared identity with other racial minorities (e.g., Craig & Richeson, 2012; Glasford & Calcagno, 2012) can be experimentally primed.

b. The problem of identity stability. However, racial identity, as conceptualized in political psychology research, might be especially stable over time (see Huddy, 2001).

To the extent that measured identity shows trait-like stability, it becomes difficult to establish causation between it and the other variables of interest, especially if those variables also show trait-like stability (cf. Kessler & Mummendey, 2002). On the other hand, there is some evidence that identity salience manipulations can shift the self-reported importance people attach to certain identities, such as national identity (Haslam et al., 1999). Similarly, a photograph-based manipulation designed to prime group pride was found to shift Asian Americans' (but not Latino Americans') self-reported closeness to and perceived linked fate with their racial group (Junn & Masuoka, 2008). That lab-based manipulations can shift measures of identification with real-world groups provides evidence that measured identity attributes might display some malleability and suggests that they could potentially change over time.

c. Identity dimensions. A related question is what aspects of group identification drive collective action or political behavior. The political psychology literature tends to measure identity as perceived closeness or similarity to the ingroup (Conover, 1984; Gurin et al., 1980; Sanchez & Vargas, 2016) or even linked fate (Gay & Tate, 1998; Simien, 2005). Some collective action researchers, on the other hand, have suggested that identity is multi-dimensional. Earlier literature refers to a cognitive component (Mummendey, Kessler, et al., 1999; van Zomeren et al., 2008) and/or an affective component (Weerd & Klandermans, 1999; van Zomeren et al., 2008). Van Zomeren et al. (2008) refer to these components as cognitive centrality (e.g., salience or importance), and affective ties to the ingroup (e.g., commitment or attachment). Some of the more recent studies use multi-dimensional measures of identity or specific subscales of a multi-dimensional identity scale, including the Identity subscale of Luthanen and Crocker's

(1992) Collective Self-Esteem Scale or a subset of its items (e.g., Major et al., 2002; Cakal et al., 2011) and versions of the Leach et al. (2008) 5-dimensional scale or specific subscales thereof (Ufkes et al., 2015; Jaśko & Kossowska, 2013, Study 2; Tran & Curtin, 2017).

Leach et al. (2008) proposed that their five identity dimensions—solidarity, satisfaction, centrality, individual self-stereotyping, and in-group homogeneity—reflect two superordinate factors, self-definition (self-stereotyping and in-group homogeneity) and self-investment (solidarity, satisfaction, centrality), which they note do not map onto the cognitive/affective distinction suggested in earlier collective action research. The Leach et al. (2008) Centrality subscale consists of items that appear similar to Luthanen and Crocker's (1992) Identity subscale, suggesting that studies using these subscales should be comparable. Furthermore, Leach et al. (2008) found that their Centrality subscale uniquely predicted perceived intergroup threat. Tran and Curtin (2017) found that the Solidarity and Centrality subscales (both of which are part of Leach et al.'s, 2008, self-investment superordinate factor) predicted Asian Americans' activism on behalf of their racial group. And Sellers and Shelton (2003) found that the Centrality scale of the Multidimensional Inventory of Black Identity (MIBI), which correlated with Luthanen and Crocker's (1992) Identity subscale, predicted perceived racial discrimination. These findings, along with van Zomeren et al.'s (2008) definition of cognitive centrality as including salience, suggest that identity centrality might be the functional component of ingroup identification connecting identity and collective action or policy support.

The collective action literature demonstrates that identity centrality can be measured in a variety of ways; however, in keeping with political psychology best practices, I used versions of Huddy, Mason, and Aarøe's (2015) partisan social identity scale, adapted to racial, POC, and American identities. This scale resembles Leach et al.'s (2008) Centrality subscale, though the authors refer to it as an identity strength scale. Because it incorporates aspects of identity that are commonly measured by political psychologists (see Huddy, 2013), using this scale connects my studies to the broader political psychology literature. Because it resembles identity centrality, which ties more closely to collective action research, using this scale is also preferable to using one of the perceived closeness or similarity measures that political psychologists tend to use. The Huddy et al. (2015) scale also has the psychometric benefits of being a multi-item scale, as opposed to a single item like many of the closeness or similarity measures used in political psychology (Huddy, 2013). Additionally, Huddy et al. (2015) explicitly link this aspect of identity to collective action motivation.

2. Perceived Discrimination

a. Perceived discrimination against self, racial/ethnic group, or POC? Besides identity, another concept that needs to be clarified is perceived discrimination. Although members of stigmatized groups tend to report less discrimination against themselves personally than against the group (e.g., Dixon, Durrheim, et al., 2010), perceived personal discrimination and perceived discrimination against the group are often treated as part of the same concept (e.g., Tropp et al., 2012; Craig & Richeson, 2012, Study 1a; Lien, 1994; Phan & Garcia, 2009). But it is possible that perceived personal and group discrimination form distinct parts of a causal chain (Dixon, Durrheim, et al., 2010) or, like individual and group relative deprivation, interact in predicting support for change (Foster & Matheson, 1995). It is also possible that perceived personal discrimination and perceived group discrimination relate differently to group identification. Branscombe, Schmitt, and Harvey (1999) suggest that attribution of personal outcomes to discrimination relates to perceived permeability of group boundaries, which, at least according to SIMCA, precedes identification (see van Zomeren et al., 2008). Perceived group discrimination, on the other hand, appears to resemble some of the injustice or group consciousness variables—namely, perceptions/appraisals of inequality, power discontent, and system blame—and has in fact substituted for system blame in some studies of group consciousness (Rodriguez & Gurin, 1990; Sanchez & Vargas, 2016).

However, whether perceived discrimination was found to precede or follow from identification does not correspond neatly to whether it was measured as personal or group discrimination. The ethnic identity development literature includes two competing theories: the rejection-identification model, in which experiences of discrimination cause the development of a stronger ethnic identity (Branscombe et al., 1999), and the identification-attribution model, in which ethnic identity increases awareness of discrimination (Gonzales-Backen et al., 2018). Support for both models comes from studies using personal discrimination measures (Branscombe et al., 1999; Fuller-Rowell, Ong, & Phinney, 2013; Sellers & Shelton, 2003; Gonzales-Backen et al., 2018). Attribution of personal outcomes to discrimination can predict ethnic identity (Branscombe et al., 1999), but it can also be predicted by ethnic identity (Major et al., 2002). Thus, there is evidence of processes in both directions with regard to personal discrimination, at least among adolescents and college students, though it is unclear whether similar processes can be expected in adults. At the same time, group discrimination has been used to prime shared identity (Craig & Richeson, 2012, Studies

2-5), suggesting that identity need not causally precede perceived discrimination against either the individual or the group. Thus, understanding the role of perceived discrimination in the relationship between identity and support for change requires answers to two questions: 1) whether perceived personal and group discrimination reflect the same underlying concept and 2) whether changes in perceived discrimination occur before or after changes in group identification.

Relatedly, at the group level, it is unclear whether perceived discrimination against the racial group and perceived discrimination against people of color should reflect the same or different concepts. Most of the existing research measures perceived discrimination against the racial or ethnic group (e.g., Dixon, Durrheim, et al., 2010; Chong & Rogers, 2005; Masuoka, 2006). A few studies have included measures of perceived discrimination against or inequality between racial groups in the abstract (Ufkes et al., 2016; Saguy et al., 2009; Levin et al., 1998, Study 1) or perceived disadvantage compared to Whites (Ufkes et al., 2016). But although Ufkes et al.'s (2016) and Levin et al.'s (1998) scale reliabilities suggest that items that mention a specific racial group can reasonably be combined with items that ask about racial inequality or discrimination in the abstract, these studies do not fully answer the question of whether perceived discrimination against ingroups at different levels of inclusiveness reflects a single concept. As discussed above, group consciousness is theoretically identity-specific, so perceived discrimination against the racial group and against people of color could be distinct to the extent that they relate to racial and POC group consciousness, respectively. But again, Rodriguez and Gurin's (1990) finding that contact with other minorities predicted perceived discrimination against the ethnic group suggests that perceptions of discrimination against both the subgroup and superordinate group could capture the same pathway from disadvantaged ingroup identity to political attitudes. Thus, it is an open question whether perceived discrimination against the self, the racial group, and people of color should be treated as a single factor or three separate factors.

b. Perceived discrimination in the collective action, group consciousness, and paradoxical effects literatures. Finally, the mechanisms for collective action and political behavior proposed in the collective action, group consciousness, and paradoxical effects literatures potentially overlap, but the nature and extent of overlap is unclear. For example, perceived discrimination measures appear in all three literatures (e.g., Major et al., 2002; Masuoka, 2006; Tropp et al., 2012; Dixon, Durrheim, et al., 2010), as do variables measuring recognition of the ingroup's disadvantages compared to a dominant outgroup (e.g., Cakal et al., 2011; Dawson, 1994; Ufkes et al., 2016). Some studies in the group consciousness tradition measured both perceived discrimination and recognition of group inequalities (alienation and deprivation, Lien, 1994; illegitimacy of subordination and power discontent, Rodriguez & Gurin, 1990). Tran and Curtin (2017) further separated perceived (personal) discrimination and structural awareness, which had been used interchangeably as measures of perceived illegitimacy or system blame (compare Gurin et al., 1980 and Rodriguez & Gurin, 1990). Levin et al. (1998) also separately measured perceived discrimination and external attributions for poverty (cf. Gurin et al.'s, 1980, original measure of system blame), though they categorized both as hierarchy-attenuating legitimizing myths.

It is therefore plausible that perceived discrimination, perceived disadvantage, and perceived injustice reflect a common underlying concept, but it is also plausible that they reflect two (e.g., perceived disadvantage as power discontent and perceived discrimination/injustice as system blame) or three distinct concepts. Additionally, collective action and group consciousness theories each suggest that this concept or set of concepts is distinct from group efficacy (van Zomeren et al., 2008; Chong & Rogers, 2005) and linked fate (Sanchez & Vargas, 2016). There also does not appear to be existing research that includes both linked fate and group efficacy in the same model. Thus, it is worthwhile to test the factor structure of all of these potential mediator variables taken together.

E. Why Use a Panel Study?

As mentioned above, most of the existing CIIM research is experimental, but much of the collective action, group consciousness, and paradoxical effects research is correlational. Within the prejudice reduction literature, the experimental focus of CIIM research contrasts with intergroup contact research, the majority of which consists of survey and field studies and only a small percentage of which consists of experiments (Pettigrew & Tropp, 2006). A correlational study of existing, real-world common ingroup identities would both test the CIIM in a more externally valid setting and provide a basis of comparison with these other literatures.

However, the correlational research to date in these areas tends to be cross-sectional, with rare exceptions (e.g., Tropp et al., 2012), limiting the ability to draw causal inferences. The policy relevance of intergroup contact research has been criticized to the extent that correlational studies fail to rule out reverse causation and other challenges to causal inference (Paluck, Green, & Green, 2019). Furthermore, a recent longitudinal study of intergroup contact failed to find evidence that contact improved outgroup attitudes or vice versa (Bohrer et al, 2019). Together with Kessler and Mummendey's (2002) finding of a lack of within-person cross-lagged effects for most of the variables in the social identity and relative deprivation models of identity-management strategy preferences, this demonstrates the importance of testing these theories with longitudinal data.

Additionally, political psychologists have tended to treat both racial identity and racial attitudes as exogenous predictors of political attitudes and behavior, but the assumptions that racial identity and racial attitudes are exogenous have rarely been tested (see Lee, T., 2008; Englehardt, 2020). Using cross-lagged panel regression, Englehardt (2020) demonstrated that not only can racial attitudes influence partisanship, but, contrary to assumptions, partisanship can shift racial attitudes. Similarly, a cross-lagged panel design makes it possible to examine the relationship over time between identity and racial attitudes, as well as between identity and support for change, to identify and compare identity-to-attitude and attitude-to-identity effects. This would both test assumptions from political psychology that seem at odds with each other (i.e., racial identity versus racial attitudes as exogenous predictor variables) and address a key weakness known to exist in correlational research on the related topic of intergroup contact effects (i.e., reverse causation between contact and intergroup attitudes; Paluck et al., 2019).

But trait-like stability, as one might expect for identity and racial attitude variables, can bias effect estimates in traditional cross-lagged panel models (CLPM; Hamaker et al., 2015). Indeed, the need to separate the roles of between-person stability and within-person change has been identified as a potential problem for intergroup contact research (Sengupta et al., 2020), particularly because the underlying theories seem to imply within-person effects (Bohrer et al., 2019). When trait-like stability is likely, Hamaker et al. (2015) recommend using a random-intercepts cross-lagged panel model (RI-CLPM) to distinguish stable, between-person relationships from cross-lagged within-person relationships. However, the traditional CLPM and RI-CLPM answer somewhat different questions: The CLPM addresses whether individual differences in one variable predict rank-order changes in the other variable between persons;[6] the RI-CLPM addresses whether within-person changes from one's trait level of one variable predict within-person changes in the other variable (Orth et al., 2021). Thus, the CLPM would test whether individual differences in identity predict changes (relative to other respondents) in an attitude, and the RI-CLPM would test whether shifts from an individual's trait level of identity predict changes in that individual's attitude. Although the within-person effects addressed by the RI-CLPM are key for identifying potential intervention targets, the CLPM also provides valuable information, i.e., for whom do identities and attitudes change and in what direction. To address identity and attitude stability and test cross-lagged relationships at both the between- and within-person levels, I use both CLPM and RI-CLPM, as recommended by Hamaker et al. (2015), to test my hypotheses about the effects of identity on racial attitudes and support for change. Figure 3 illustrates using RI-CLPM to test Hypothesis 2; for comparison, part b of Figure 1

[6] However, these rank-order changes could reflect both between-person and within-person shifts in the predicted variable, and the CLPM cannot distinguish between the two (see Hamaker et al., 2015).

illustrates the CLPM version. (Again, the hypothesized paths—in this case, within-person effects of identity on attitudes—are in bold.)

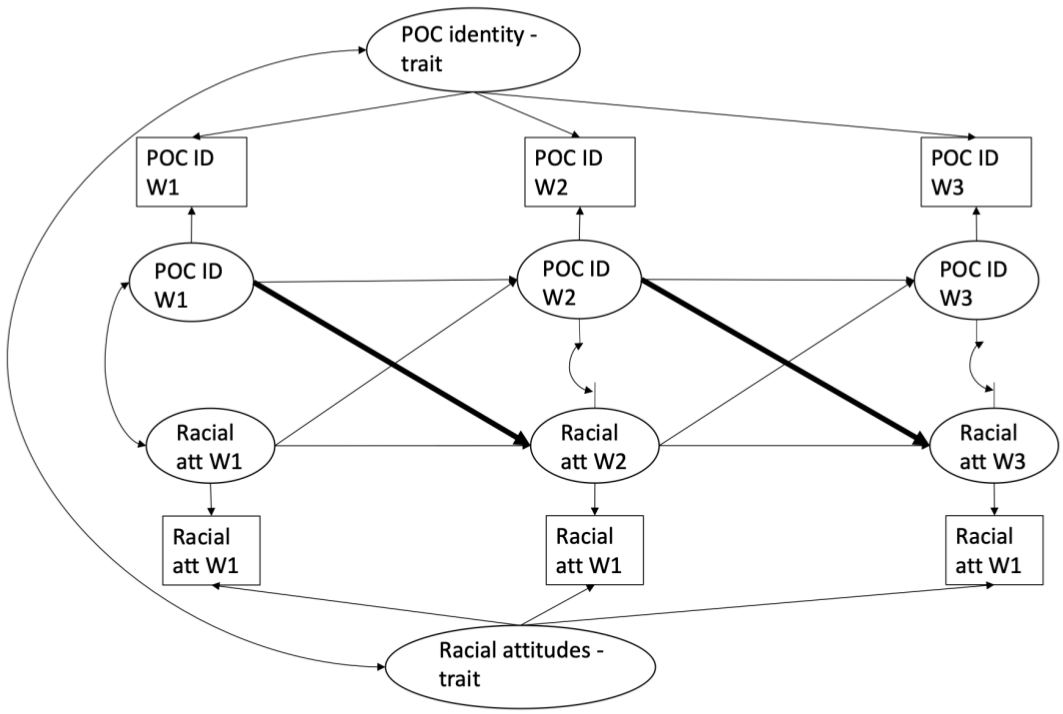


Figure 3. RI-CLPM for Hypothesis 2. Hypothesized paths are in bold.

Finally, causal inference from cross-sectional correlational data can be especially problematic with mediation models (Maxwell & Cole, 2007). Mediation models pose problems for experiments as well, particularly when mediators are measured rather than manipulated (e.g., Bullock, Green, & Ha, 2010). To address some of these causal inference concerns, I plan to use a 3-wave panel design combined with Cole and Maxwell's (2003) strategy for longitudinal mediation analysis.

F. Why Asian Americans?

Asian Americans are an under-studied population in social and political psychology (see, e.g., Tran & Curtin, 2017). At the same time, as a group that has been portrayed as both not White and not Black, with the relative importance of these distinctions fluctuating over time (Wu, 2014), Asian Americans could differ from other minority groups when it comes to identity, perceived discrimination, and politicization.

There are reasons to expect Asian Americans to be relatively unlikely to both identify strongly as people of color (though this identity is available to them) and challenge the status quo. First, Asian Americans may not perceive themselves as part of a stigmatized group. Some evidence suggests that Asian and Latino Americans perceive race as less of a social problem than African Americans do (Masuoka, 2006) or do not connect their experiences of racial discrimination to their political choices (Junn & Masuoka, 2008). Others have suggested that some Asian groups in the West (e.g., Chinese Canadians) objectively do not experience group-based disadvantage (Goodyear-Grant & Tolley, 2019). To the extent that shared discrimination is important to POC identity (e.g., Craig & Richeson, 2012), Asian Americans who perceive no discrimination against their racial group would be less likely to identify as people of color. And if they do not see themselves as disadvantaged by the status quo, they are unlikely to be motivated to challenge it.

Second, Asian Americans experience what Kim (1999) terms "racial triangulation," a process by which their status in society is defined in comparison to both Whites and Blacks. Relatedly, as part of the struggle to gain acceptance in the 1950s and 1960s, Japanese and Chinese American leaders contributed to the development of the model minority myth, which has since been used to reinforce individual mobility beliefs and shape the racial status hierarchy (Wu, 2014). The model minority myth contrasts positive stereotypes of Asian Americans with negative stereotypes of African Americans and sometimes Latino Americans (Wu, 2014), and it continues to resurface as a wedge between Asian Americans and other people of color. For example, media portrayals of the 1992 Los Angeles riots described a conflict between poor Black residents and hardworking Korean immigrants (Lee, E., 2015; Wu, 2014), and coverage of the aftermath of Hurricane Katrina contrasted Vietnamese residents' rapid recovery with Black residents' need for assistance (Wu, 2014). These kinds of narratives could make it difficult for some Asian Americans to perceive a shared POC identity. Furthermore, even if Asian Americans identify as POC, the portion of the model minority myth that depicts them as apolitical (in contrast to African Americans) could discourage activism by signaling that "Asian Americans have 'much to lose if they decide to join other politically active minority groups.'" (Kim, 1999, p. 119).

At the same time, Asian Americans have the highest rate, among racial minorities, of residential integration with Whites (Lien et al., 2004) and a relatively high rate of intermarriage with Whites (Zhou, 2004), and Asian-White biracial children are more likely to be classified as White than Black-White biracial children (Bonilla-Silva, 2004). These facts have led some to ask whether Asian Americans or a subset of Asian Americans are "becoming white" (Zhou, 2004) or becoming part of a new "honorary white" group in the American racial hierarchy (Bonilla-Silva, 2004). To the extent that Asian American individuals internalize this aspiration to whiteness, the group boundary with Whites might seem permeable enough to keep both racial identification and POC identification low.

Additionally, like Latino Americans, Asian Americans are a culturally heterogeneous group with relatively little shared history in the United States, and these factors make development of Asian American group consciousness less likely (e.g., Masouka, 2006). Furthermore, contrary to the model minority myth, Asian Americans "are overrepresented at both ends of the educational and socioeconomic spectrum" (Lee, E., 2015, p. 376). This socioeconomic heterogeneity could be a further barrier to Asian American linked fate because Asian Americans do not have the shared history of economic disadvantage and institutions like Black churches that help reinforce African American linked fate in spite of intragroup socioeconomic disparities (Dawson, 1994). In fact, Masuoka (2006) found that nearly half of the Asian American respondents in the 2000 Pilot National Asian American Political Survey perceived no linked fate with other groups of Asian Americans. At the same time, nearly half of Asian Americans reported no partisan affiliation or indicated that they do not think in terms of political parties (Phan & Garcia, 2009; Lien et al., 2004), in contrast to African Americans' nearly universal support for the Democratic party (Dawson, 1994), and this suggests relatively low political solidarity in at least this one area of political behavior.

Asian Americans' (and Latino Americans') willingness to express racial group attachment or use race in political decision-making might be further constrained by relatively widespread endorsement of colorblind ideology (Junn & Masuoka, 2008). Similarly, Asian American individuals' endorsement of the model minority myth has been found to predict less own-group activism (Tran & Curtin, 2017). Tran and Curtin (2017) theorized that this effect occurs because the model minority myth supports individual mobility beliefs, legitimizes the racial status quo, and prompts comparisons with other marginalized groups (presumably rather than prompting comparisons with Whites). Endorsement of colorblind ideology could likewise reflect individual mobility beliefs and judgments that the status quo is legitimate (cf. Sengupta & Sibley's, 2013, finding that endorsement of meritocracy mediates the relationship between contact with the dominant group and reduced support for social change). And endorsement of certain status quo-legitimizing ideologies could be positively associated with Asian American identification (Levin et al., 1998), further complicating the relationship between identity and support for change. Thus, racial and POC identity and the SIT socio-structural factors could all be barriers to Asian American activism.

Furthermore, key policies addressing racial inequality might seem less relevant to Asian Americans or even be framed in ways that exclude them. Affirmative action is one such policy area. Asian Americans are classified with Whites rather than with other minority groups for at least some equal opportunity programs (Zhou, 2004), even though they are a protected group under U.S. Department of Labor guidelines (see Weathers & Truxillo, 2008). Perhaps because of this ambiguity of classification and/or the prevalence of the model minority myth, both White and Asian Americans tend to perceive Asian Americans as not benefitting from affirmative action compared to other minority groups (Weathers & Truxillo, 2008). In the context of college admissions, in particular, what began as questions about whether universities used quotas on Asian American students to maintain their existing proportion of White students became a question of whether affirmative action programs benefitting other racial minorities discriminate against Asian Americans (Kim, 1999). And the narrative that affirmative action in college admissions harms Asian Americans has cropped up in high profile lawsuits (Students for Fair

Admissions, 2018), in media coverage of these lawsuits (e.g., Jung, 2018), and in Asian Americans' own conversations about their attitudes toward affirmative action (Inkelas, 2003). As a result, one might expect highly identified Asian Americans to express ambivalence or even opposition to affirmative action, especially if they perceive high levels of linked fate with other Asian Americans. On the other hand, Asian Americans who perceive more discrimination might have more favorable attitudes toward affirmative action (Bell, 1997). And to the extent that support for affirmative action has declined among Asian Americans recently, this has primarily been among Chinese Americans and in particular, foreign-born Chinese Americans (Leung & Song, 2021). If the broader Asian American population tends to support affirmative action, then Asian American identity might be positively associated with support for affirmative action (though Chinese identity might have the opposite effect). Nonetheless, because of their unique position with regard to this issue area, Asian Americans' attitudes toward affirmative action are difficult to predict based on their racial identification alone, and they could potentially diverge from other racial minorities' attitudes.

Despite these challenges to Asian American and POC identification and solidarity, however, Asian Americans do express pan-ethnic identification (Lien, Conway, & Wong, 2003) and linked fate with other Asian Americans (Masuoka, 2006; Junn & Masuoka, 2008), though the predictors of Asian American linked fate might differ from predictors of African American linked fate (Junn & Masuoka, 2008). Furthermore, Asian Americans show relatively high levels of solidarity in policy preferences, including—perhaps unexpectedly—support for affirmative action (Lien et al., 2004). Despite the model minority myth, Asian Americans have a history of activism, including the adoption of "Asian American" as an identity (Wu, 2014; Lee, E., 2015). And much of that history of activism has been coalition-based (Marisol Meraji & Demby, 2020), as perhaps exemplified by the 1968 San Francisco State College strike, which was led by the Third World Liberation Front (comprised of Asian, Chicano, and Native American student organization; see Lee, E., 2015) and the Black Student Union (Marisol Meraji & Demby, 2019). It is useful, then, to understand when Asian Americans display solidarity and activism.

G. Putting It Together

Collective action theory and group consciousness theory already predict that racial identity increases support for social change that benefits the racial group. These effects should appear in policy areas that have been connected to the racial group in some way. Because recent calls for criminal justice reform are intertwined with the issues raised by the Black Lives Matter movement (see, e.g., Ghandnoosh, 2015), this should be a policy area in which African Americans' racial identity is a strong predictor. Although Latinos are also impacted by racial disparities in criminal justice (e.g., Ghandnoosh, 2015), the association between criminal justice reform and Black Lives Matter could limit the extent to which Latino Americans connect this issue to their own racial group and thus the extent to which racial identity predicts their support for criminal justice reform. Similarly, the originally intended and prototypical beneficiaries of affirmative action are Black (see Capers & Smith, 2016), suggesting that racial identity should predict African Americans' support for affirmative action. However, Latino Americans might also perceive their group as benefitting from these policies (which could explain Capers and Smith's, 2016, finding that Latino immigrants report as much support for affirmative action as Afro-Caribbean immigrants do—though less than African Americans—and more than Asian immigrants or Whites do). As a result, racial identity should also predict Latino Americans' support for affirmative action. (As discussed in the Chapters 2 and 4, however, these two hypotheses are not tested because Study 2, which included Black and Latino respondents, did not include questions about affirmative action.) Because Latino and Asian Americans are relatively "new" immigrant groups (e.g., Masuoka, 2006), immigration policy has the potential to affect individuals in these groups or their families or close friends directly, and thus, racial identity should predict more liberal immigration attitudes for these groups. The effects of racial identity on own-group policy attitudes should be mediated by linked fate with the racial group, perceived discrimination against the racial group (or perceived discrimination, disadvantage, or illegitimacy more generally), and racial group efficacy.

The more novel hypothesis is that POC identity increases racial minorities' support for social change that benefits other racial minority groups via the same collective action and group consciousness mechanisms. In other words, POC identity can increase recognition of inequality with Whites, perception of linked fate with other people of color, and POC political efficacy, and as a result, increase support for social change that benefits people of color as a whole. As discussed above, Asian Americans' racial identity might predict ambivalence or even opposition to affirmative action, especially through the racial group linked fate pathway, to the extent that they perceive their group as not benefitting from or even being harmed by affirmative action. POC identity, on the other hand, should predict support for affirmative action through the linked fate pathway (because it benefits people of color) as well as the perceived discrimination pathway (because it addresses existing and past discrimination against POC). Similarly, non-immigrant African Americans tend to hold immigration attitudes that are more similar to Whites' than to Black, Latino, and Asian immigrants' attitudes (Capers & Smith, 2016), suggesting that African Americans' racial identity should not predict more liberal immigration attitudes. But POC identity should predict more liberal immigration attitudes to the extent that African Americans perceive immigrants of color as part of the superordinate identity. A weaker version of this effect might occur for Asian Americans, who have not been as explicit a target of recent immigration policies (e.g., the border wall) as Latino Americans have been and thus could potentially shift their immigration attitudes in solidarity with Latino immigrants. I also expect POC identity to increase Asian and Latino Americans' support for criminal justice reform, in solidarity with African Americans, who are more visibly affected by current racial disparities in criminal justice. Thus, POC identity would predict African Americans' support for more liberal immigration policies, Latino and Asian Americans' support for criminal justice reform, and Asian Americans' support for affirmative action. These effects should be mediated by linked fate with people of color, perceived discrimination against people of color (and/or perceived illegitimacy of the racial status quo), and POC group efficacy.

As discussed above, American identity should predict less support for change across all three policy areas, but the set of mechanisms should be more limited than those for racial and POC identities. To the extent that higher identification as American does not correspond to lower racial or POC identification, the existing literature does not suggest mediation through racial or POC group efficacy or linked fate. On the other hand, I expect the effects of American identity to be partially mediated by lower perceived discrimination, disadvantage, and/or illegitimacy of the racial status quo, as high identifiers might make fewer comparisons with Whites or perceive predominantly White authorities as fairer than low identifiers do.

Combining the collective action hypotheses (Hypotheses 5-7) and the group consciousness hypotheses (Hypotheses 8-10) with predictions about what policy areas are likely to be perceived as relevant to each racial group leads to specific hypotheses for Asian, Black, and Latino Americans. These specific hypotheses are presented in Chapter 2 in the context of the studies in which I test each hypothesis.

Chapter 2: Overview of Studies

My research consists of two 3-wave panel studies carried out between October and December 2020. The purposes of these studies were as follows:

1. Test predictions from the common ingroup identity model (CIIM) in a context that is novel in at least three respects: 1) I focus on inter-minority group attitudes instead of majority group members' attitudes toward a minority group and minority group members' attitudes toward the majority group. 2) I examine common ingroups at two different levels of inclusion (American and POC). 3) I measure chronic identity salience (identity importance or identity centrality) over time instead of priming identity in a one-time experiment. The longitudinal nature of the data also allows me to test for reverse effects (racial attitudes → group identification) and trait-like stability among these variables.
2. Replicate the so-called "paradoxical" effects (e.g., Dixon et al., 2010a) of prejudice reduction (i.e., reduced support for social change) with a common ingroup identity that includes the dominant group (i.e., American) in a longitudinal context. Extend this research by testing whether these effects also occur for policies that affect other minority groups.
3. Replicate findings from collective action theory and group consciousness theory that racial identity (e.g., Asian American identity) predicts increased support for social change that improves the racial group's position. Also test potential mediators of this effect (drawn from research on collective action, group consciousness, and paradoxical effects of prejudice reduction): 1) attitudes toward

Whites, 2) attention to inequality (and/or perceived discrimination/group position aspects of group consciousness), 3) group efficacy, 4) linked fate.

4. Test whether stronger identification with a common ingroup that does not include the dominant group (i.e., POC) predicts increased support for social change, i.e., whether it has the opposite effect of American identity. This effect would indicate a boundary condition (whether or not the common ingroup includes the majority group) for paradoxical effects and would extend collective action and group consciousness theories to a superordinate level of identity.
5. Test whether the collective action and group consciousness models from point 3 above explain the effects of POC and American identities on support for social change. These mechanisms would more explicitly connect the CIIM and paradoxical effects of prejudice reduction to the literatures on disadvantaged groups' support for change.

Study 1 focused on Asian Americans and consisted of online surveys given at 3-4 week intervals between November 9, 2020 (the Monday after the results of the U.S. Presidential election were announced in most news outlets) and January 2, 2021 (before the January 6th insurrection). This time frame was chosen to capture attitudes during a period when politics should have been relatively less salient than they had been leading up to the election and political attitudes among the general public should thus have been more similar to what they normally are, though this expectation might not have been met due to the unique circumstances of the 2020 election and its aftermath. Study 2 used data from Black and Latino respondents in the University of Minnesota Center for the Study of Political Psychology's (CSPP) 2020 Presidential Election Study, a large, multi-investigator study with data collection at 1- to 2-week intervals before (Wave 1: Oct. 5-Oct.13; Wave 2: Oct. 26-Nov. 3) and after the election (Wave 3: Nov. 9-16).

Because Asian Americans had not been studied as extensively as other groups in the literature on prejudice reduction, collective action, or group consciousness, I ran a pilot study with Asian American respondents from the same survey platform (Prolific, prolific.co) that I would later use for Study 1. The purposes of the pilot study were 1) to test the psychometric properties of the identity and policy attitude items I planned to use in Study 1 that had not previously been used in surveys of Asian Americans and 2) to examine the factor structure of the potential mediator items for Asian Americans. The latter was particularly important because of evidence that group consciousness and linked fate have different factor structures for Black, Latino, and Asian Americans (Sanchez & Vargas, 2016). The pilot study also tested whether certain demographic and political variables were associated with the identity and policy variables of interest and, to the extent that they were not, allowed me to omit those items from Study 1. The pilot study is described in the first part of Chapter 3.

A. Study 1

Study 1 measured racial, POC, and American identities; racial attitudes; attitudes toward policies associated with particular racial minority groups; and potential mediator variables at three time points. Identities were measured in three ways: 1) an item that asked respondents to rank several identities, including the three target identities (Asian American, POC, and American), in order of how strongly the respondent identifies with each; 2) a checklist of which identities (again, including the three target identities) respondents consider important to who they are; and 3) versions of the 4-item Huddy et al. (2015) identity scale, re-written for each of the three target identities. Racial attitudes were measured using feeling thermometers and two 7-point stereotype items (lazy-hardworking and unintelligent-intelligent), with Whites, Blacks, and Hispanics/Latinos as the target groups. (Items with Black and Hispanic/Latino target groups were combined for analyses into a nonwhite feeling thermometer score and a nonwhite stereotype score.) Policy attitude items fell into three policy areas: immigration (3 items), criminal justice reform (3 items), and affirmative action (2 items). Potential mediator items included group political efficacy (2 items for Asian Americans, 2 items for POC), linked fate with Asian Americans and with POC, perceived discrimination (against Asian Americans, against POC, and against oneself), and 4 additional items that broadly relate to group-based relative deprivation.

The main purposes of this study were to examine the over-time relationship between 1) POC and American identities and racial attitudes (testing and extending the CIIM) and 2) racial, POC, and American identities and policy attitudes (testing and extending the research on collective action/group consciousness and paradoxical effects of prejudice reduction). Because other racial minority groups are included in the POC common ingroup, I expected higher POC identification to predict improvements in attitudes toward Blacks and Latinos (i.e., increases in feeling thermometer and stereotype ratings of these groups). Because other racial minority groups and Whites are included in the American common ingroup, I expected higher American identification to predict improvements in attitudes toward Blacks and Latinos and improvements in attitudes toward Whites.

My hypotheses regarding policy attitudes differed for own-group and other-group policy areas. As I noted in Chapter 1, I expected Asian Americans to think about immigration as an issue affecting their own racial group and to think about criminal justice reform and affirmative action as issues affecting other racial minority groups. For the own-group issue of immigration, I expected based on the collective action literature that racial identity (i.e., identification as Asian American) would predict changes in immigration attitudes in favor of more liberal policies. For the other-group issues of criminal justice reform and affirmative action, I expected based on the dynamic dual pathway model (van Zomeren et al., 2012) that POC identity would make these policy areas self-relevant and would therefore predict increases in support for policies that benefit other racial minority groups (i.e., increases in support for criminal justice reform and affirmative action). I did not expect racial identity to predict attitude changes in these two issue areas: To the extent that they are not perceived as relevant to Asian Americans, self-categorization as an Asian American would not make these issues self-relevant. On the other hand, I expected based on the paradoxical effects literature that American identity would predict decreases in support for policies that benefit both respondents' own group and other minority groups to the extent that this common ingroup identity increases perceptions of the dominant group and society as a whole as fair or just (see Dovidio et al., 2016).

Thus, the main hypotheses I tested in Study 1 were

Hypothesis 1: A common ingroup identity that includes the dominant group (American identity) predicts more positive attitudes toward other racial minority groups and toward Whites.

Hypothesis 2: A common ingroup identity that does not include the dominant group (POC identity) predicts more positive attitudes toward other racial minority groups.

Hypothesis 11: Asian American identity predicts more liberal immigration attitudes.

Hypothesis 12: For Asian Americans, POC identity predicts increased support for affirmative action and criminal justice reform.

Hypothesis 13: American identity predicts less liberal immigration attitudes and decreased support for affirmative action and criminal justice reform.

To test these hypotheses, I used cross-lagged panel models (CLPM) and random-intercepts cross-lagged panel models (RI-CLPM) to examine the cross-lagged effects of each identity on each measure of racial or policy attitudes at the between-person and within-person levels. The CLPM allowed me to test whether between-person differences in identity at an earlier time point predict changes in an attitude from the earlier time point to a later time point, though as discussed in Chapter 1, cross-lagged coefficients in those models reflect a combination of between-person (rank-order) and within-person attitude changes. The RI-CLPM allowed me to test whether within-person deviations from individuals' trait levels of identity at an earlier time point predict within-person changes in the attitude from the earlier time point to a later time point. As discussed in Chapter 1, Figure 1 illustrates the CLPM for Hypotheses 1 and 2; Figure 3 illustrates the

RI-CLPM for Hypothesis 2. The models for Hypotheses 11-13 take the same form but with different identities and with specific policy attitudes instead of racial attitudes. With 3 waves of data, I also examined whether the stationarity assumption was justified for each identity-attitude pair (see Hamaker et al., 2015) by fitting a model in which each lagged or cross-lagged effect from Wave 1 to Wave 2 was constrained to be equal to that effect from Wave 2 to Wave 3 and comparing the fit of the constrained and unconstrained models. This was done for both the CLPM and the RI-CLPM.

I also tested mediation hypotheses based on the collective action, group consciousness, and paradoxical effects literatures. As described in more detail in Chapter 3, I aggregated the potential mediator items into four factor scores: efficacy, linked fate, perceived discrimination, and relative deprivation, and I used longitudinal mediation models to test the mediation hypotheses. Based on the collective action and group consciousness literatures, I expected the effects of racial identity on own-group policy attitudes to be mediated by increases in group efficacy, linked fate, perceived discrimination, and relative deprivation. Similarly, I expected the effects of POC identity on other-group policy attitudes to be mediated by increases in group efficacy, linked fate, perceived discrimination, and relative deprivation. Based on the paradoxical effects literature, I expected the effects of American identity on both own- and other-group policy attitudes to be mediated by decreases in perceived discrimination and relative deprivation (which also correspond to the injustice pathway in the SIMCA, van Zomeren et al., 2008) and potentially linked fate and group efficacy. However, as discussed in Chapter 1, the linked fate and group efficacy pathways are less well-supported empirically and less justifiable theoretically when dual identification is possible. Thus, the mediation hypotheses I tested in Study 1 were

Hypothesis 14: The effect of Asian American identity on immigration attitudes is (partially) mediated by increases in group efficacy, linked fate, perceived discrimination, and relative deprivation.

Hypothesis 15: The effects of POC identity on attitudes toward criminal justice reform and affirmative action are (partially) mediated by increases in group efficacy, linked fate, perceived discrimination, and relative deprivation.

Hypothesis 16: The effects of American identity on attitudes toward immigration, criminal justice reform, and affirmative action are (partially) mediated by decreases in perceived discrimination and relative deprivation.

These hypotheses were tested using longitudinal mediation models (Cole & Maxwell, 2003). However, there is no reason to expect that direct effects of identity on policy attitudes need to take the same amount of time as indirect effects; thus, I used the model from Maxwell, Cole, and Mitchell's (2011) Figure 1 and defined direct effects from Wave 1 identities to Wave 2 policy attitudes and from Wave 2 identities to Wave 3 policy attitudes. I first fit a full model that included an identity, a mediator, and a policy attitude at all three time points, paths from every variable in Wave 1 to every variable in Wave 2, and paths from every variable in Wave 2 to every variable in Time 3. With 3 waves of data, I was able to test the stationarity assumption (Cole & Maxwell, 2003) by constraining all Wave 1-2 paths to be equal to their Wave 2-3 counterparts and comparing the fit of the constrained and full models. For illustration, Figure 4 presents the constrained mediation model with POC identity as the predictor, linked fate as the mediator, and criminal justice attitudes as the response variable (i.e., part of Hypothesis 15). Paths are labeled using Cole and Maxwell's (2003) letter scheme: *x*, *m*, and *y* paths indicate autoregressive effects for the predictor, mediator, and response variable, respectively; *a* paths indicate cross-lagged effects of the predictor on the mediator; *b* paths indicate cross-lagged effects of the mediator on the response variable; and *c* paths indicate direct effects of the predictor on the response variable. Dotted lines indicate paths in the opposite direction of the hypothesized paths, which were included in the full and stationarity models but are marked with dotted lines and not labeled in the figure in order to more clearly present the hypotheses. I also fit a third model without the reverse paths (the dotted lines in Figure 4) and without stationarity and compared the fit of this model with the unconstrained model. My hypothesized indirect effects were defined as the product, *ab*, of the *a* path from Wave 1 to Wave 2 and the *b* path from Wave 2 to Wave 3 in the relevant mediation model.

Thus, Study 1 tested my hypotheses about direct effects and indirect effects among Asian Americans. Study 2 extended my analyses by testing a subset of these hypotheses among Black and Latino Americans.

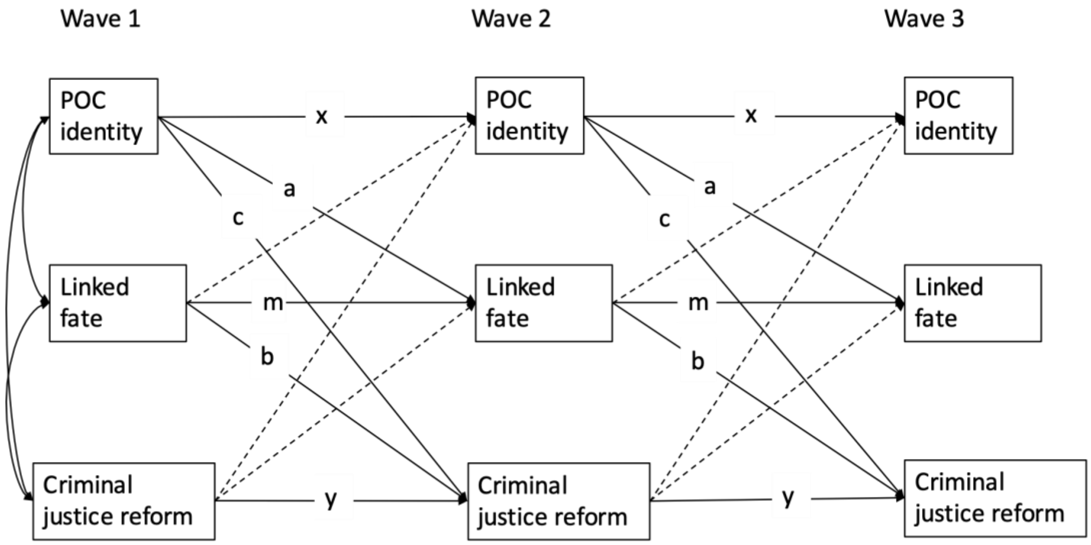


Figure 4. Proposed mediation model for a portion of Hypothesis 15, with linked fate as the mediator and support for criminal justice reform as the dependent variable. This model assumes stationarity of lagged and cross-lagged effects across the Wave 1-2 and Wave 2-3 time lags. Autoregressive effects are denoted *x, m*, and *y*. Cross-lagged effects are denoted *a*, *b*, and *c*. Direct effects are the cross-lagged *c* paths. The indirect effect of interest is the product of the cross-lagged *a* path from Wave 1 to Wave 2 and the cross-lagged *b* path from Wave 2 to Wave 3. Dashed lines indicate cross-lagged reverse effects, which were not part of my hypothesis.

B. Study 2

Study 2 consisted of a set of items on the University of Minnesota Center for the Study of Political Psychology's (CSPP) 2020 Presidential Election Study. The CSPP study involved a representative sample of eligible voters in the United States, plus an oversample of Black respondents, recruited through YouGov. Study 2 used the data from the Black and Latino respondents. Identification with each of the three key target groups (racial group, POC, and American) was measured using a 2-item version of the Huddy et al. scale. Racial attitude measures consisted of feeling thermometers of Whites, Blacks, Hispanics/Latinos, and Asian Americans. For Black respondents, the Hispanic/Latino and Asian American feeling thermometer ratings were aggregated into a composite score for "other minority groups"; for Latino respondents, this composite variable consisted of the ratings of Blacks and Asian Americans. Policy attitude measures consisted of two items on immigration, an item on mandatory minimum sentences, and items asking about respondents' attitudes toward Black Lives Matter and the protests after the police killing of George Floyd. I treat the last three items as measures of criminal justice reform attitudes for the purpose of my hypotheses and conclusions. Study 2 also included measures of linked fate with respondents' racial group and with POC.

Again, I used cross-lagged panel models (CLPM) and random-intercepts cross-lagged panel models (RI-CLPM) to examine the cross-lagged effects of each identity on each measure of racial or policy attitudes. I also tested the stationarity assumption using the same approach as in Study 1. I analyzed the data from Black respondents and the data from Latino respondents separately.

As in Study 1, I expected based on the CIIM that POC identity would predict improvements in attitudes toward other racial minority groups and that American identity would predict improvements in attitudes toward other racial minority groups and Whites. These effects should be present for both Black and Latino respondents. Thus, Study 2 also tests the following hypotheses:

Hypothesis 1: A common ingroup identity that includes the dominant group (American identity) predicts more positive attitudes toward other racial minority groups and toward Whites.

Hypothesis 2: A common ingroup identity that does not include the dominant group (POC identity) predicts more positive attitudes toward other racial minority groups.

I expected immigration to be an own-group policy area for Latino respondents and an other-group policy area for Black respondents. Conversely, as discussed in Chapter 1, I expected criminal justice reform to be an own-group policy area for Black respondents and an other-group policy area for Latino respondents (because of the association between criminal justice reform and Black Lives Matter in the recent discourse). Accordingly, racial identity should predict changes in immigration attitudes in favor of more liberal policies for Latino respondents and increases in support for criminal justice reform among Black respondents (i.e., increases in support for own-group policies). POC identity should predict changes in immigration attitudes in favor of more liberal policies for Black respondents and increases in support for criminal justice reform among Latino respondents (i.e., increases in support for other-group policies). As with Asian Americans in Study 1, I expected American identity to predict less liberal immigration attitudes and decreases in support for criminal justice reform for both groups of respondents in this study (i.e., Hypothesis 13). Spelled out separately for each respondent group, these hypotheses are

Hypothesis 17: Hispanic/Latino identity predicts more liberal immigration attitudes.

Hypothesis 18: Black identity predicts increased support for criminal justice reform.

Hypothesis 19: For African Americans, POC identity predicts more liberal immigration attitudes.

Hypothesis 20: For Hispanic/Latino Americans, POC identity predicts increased support for criminal justice reform.

Hypothesis 13: (same as for Asian Americans in Study 1) American identity predicts less liberal immigration attitudes and decreased support for criminal justice reform.

Because the only potential mediator variables included in Study 2 were the linked fate items, mediation analyses were more limited in this study. As in Study 1, I expected linked fate to mediate the effects of racial identity and POC identity on policy attitudes. But again, linked fate seemed like a more tenuous mediator for the effects of American identity. Additionally, to the extent that linked fate and group consciousness represent a single concept for African Americans but not for Latinos (Sanchez & Vargas, 2016), the linked fate mediator could potentially capture effects of unmeasured group consciousness variables for Black respondents but not for Latino respondents. In other words, linked fate could be a significant mediator in models for Black respondents even if a different aspect of group consciousness is the actual mechanism, but the same would not be true for Latino respondents. As a result, it was plausible that I would find indirect effects via linked fate for Black respondents but not Latino respondents. Thus, my mediation hypotheses for Study 2 are as follows:

Hypothesis 21: The effect of Black identity on support for criminal justice reform is (partially) mediated by linked fate.

Hypothesis 22: For African Americans, the effect of POC identity on immigration attitudes is (partially) mediated by linked fate.

Hypothesis 23: (tentative) The effect of Hispanic/Latino identity on immigration attitudes is (partially) mediated by linked fate.

Hypothesis 24: (tentative) For Hispanic/Latino Americans, the effect of POC identity on support for criminal justice reform is (partially) mediated by linked fate.

These hypotheses were tested using the same modeling strategy as in Study 1.

Chapter 3: Study 1

Study 1 was a 3-wave online panel study of Asian Americans that measured Asian American, POC, and American identity, potential mediators, racial attitudes, and attitudes toward three different policy areas: immigration, criminal justice reform, and affirmative action. The main purpose of this study was to test whether, for Asian Americans, American and POC identities predict more positive attitudes toward other racial minority groups (Hypotheses 1 and 2), American identity predicts less support for policies associated with racial minorities (Hypothesis 3), and POC identity predicts more support for policies associated with racial minorities (Hypothesis 4), controlling for the stability of each variable and attitude-to-identity "reverse" effects. I used cross-lagged panel models and random intercepts cross-lagged panel models to test these hypotheses. An additional purpose of Study 1 was to test, using longitudinal mediation models, whether linked fate, group political efficacy, perceived discrimination or injustice, and/or attitudes toward Whites mediate effects of Asian American (i.e., own racial subgroup), POC, and American identities on support for groups and policies that challenge the racial status quo (Hypotheses 12, 15, and 18).

A. Pilot Study

Before running the main study, I pilot tested identity, policy, and potential mediator items with a smaller online sample of Asian Americans. This pilot study served two purposes: 1) to check the psychometric properties of identity and policy items that had not been validated in prior research and 2) to explore the relationship among group efficacy, linked fate, and group consciousness variables for Asian Americans. Because there is evidence that the relationship between linked fate and other group consciousness variables differs across racial groups (Sanchez & Vargas, 2016), it is important to understand how measures of these constructs, as well as group efficacy, hang together for Asian Americans specifically before they can be analyzed as mediators in a study of Asian Americans.

1. Method

Respondents. Respondents were Asian American adults recruited through Prolific (prolific.co) in October 2020 using two demographic filters: ethnicity = Asian and nationality = United States. Out of 307 respondents who consented to take part in the study, 297 self-identified their race as Asian. An additional 6 respondents self-identified as Other, but because they specified “South Asian,” “Asian American,” or an Asian ethnic group, their responses were included in my analyses, giving a total sample size of 303.

Most respondents self-identified only as Asian (or Other), but 3 also identified as White, 2 also identified as American Indian or Alaskan Native, and 2 also identified as Native Hawaiian or Pacific Islander. The most common ethnic subgroups were Chinese (N = 110), Vietnamese (N = 50), Indian (N = 39), Filipino (N = 33), and Korean (N = 31). As expected based on the screening criteria, most respondents were U.S. citizens (298 citizens, 3 non-citizens). Perhaps because of the nationality criterion, a large majority of respondents were born in the U.S. (215 respondents, or 71%). One hundred sixty respondents identified as male, 137 identified as female, and 3 identified as non-binary or gender non-conforming. Respondents were relatively young on average (Mean = 26.9, SD = 8.7), but they ranged in age from 18 to 62. They also tended to be well-educated (171, or 57% of respondents who responded to this item, had at least a 4-year college degree) and have somewhat high incomes (median = \$60,000-69,999; modes = \$50,000-59,999, \$80,000-99,999, \$100,000-149,000).

Materials and Procedure. Respondents completed a one-time survey including measures of identity, attitudes related to immigration and criminal justice reform, linked fate, group efficacy, perceived discrimination, and perceived disadvantage or inequality (see Appendix A for items).[1] The order in which the identity, policy, and potential mediator items were presented was randomized to control for order effects.

Identity measures. Three types of social identity measures were used. First, respondents were asked to rank five identities—individual, ethnic group (e.g., Chinese), Asian American, person of color, and American—in order of how strongly they identify with each. Next, respondents were asked to check which of the five identities they consider important to who they are. Finally, they were given a version of the 4-item Huddy et al. (2015) scale for each of the three identities of interest (in random order): Asian American, person of color, and American. Thus, for each of these three identities, each respondent had an importance ranking, a binary variable indicating whether or not they selected the identity as important, and responses to the 4 items of the Huddy et al. identity centrality scale.

Policy attitude measures. Policy attitude measures were a combination of items that have appeared on other surveys and new items written for this study. I pilot tested three items related to immigration and three items related to criminal justice reform. For immigration, respondents were asked 1) their opinion on the number of immigrants who

[1] Internal consistency (α) is provided for the final scales after the psychometric analyses in the Results section, below.

should be allowed to enter the U.S. (1 = decreased a lot; 5 = increased a lot); 2) the extent to which they favor allowing undocumented immigrants to stay in the U.S. versus deporting them (1 = strongly favor deportation; 4 = strongly favor allowing them to stay); and 3) the extent to which they favor or oppose detaining undocumented migrants at the border (1 = strongly oppose; 5 = strongly favor). The first item appeared on the University of Minnesota Center for the Study of Political Psychology (CSPP) 2016 Presidential Election Panel Study, the second item is a modified version of an item from the 2016 CSPP study, and the third item was written for this study based on events of the last few years. For criminal justice reform, respondents were asked 1) whether they think there are too many people in prison, too few people in prison, or about the right number of people in prison in the U.S.; 2) the extent to which they favor or oppose proposals to defund police departments and redirect funds to alternative kinds of first responder services (1 = strongly oppose, 5 = strongly favor); and 3) the extent to which they favor or oppose eliminating mandatory minimum sentences for some crimes (1 = strongly oppose, 5 = strongly favor). The first item was adapted from a survey of Massachusetts voters' opinions on criminal justice reform (Koczela & Parr, 2017); the other two items were written for this study. The order of the two sets of policy items was randomized, as was the order of the items within each policy area.

Potential mediators. I pilot tested a variety of items tapping linked fate, group consciousness, relative deprivation, and group efficacy.

Linked fate with Asian Americans and people of color was measured with a set of two items each: "Do you think what happens generally to other [Asians/people of color] in this country affects what happens in your life?" and if the respondent answered yes, "Will it affect you a lot, some, or not very much?" These items were collapsed into a single score for Asian American linked fate and a single score for POC linked fate (1 = No, 2 = Not very much, 3 = Some, 4 = A lot).

Group efficacy was measured, separately for Asian American and POC ingroups, using adapted versions of two external political efficacy items: "How much do public officials care about what [Asian Americans/people of color] think?" and "How much can [Asian Americans/people of color] affect what the government does?" Both items are measured on a 5-point scale from "not at all" to "a great deal." I used political efficacy for two reasons: 1) Because I am studying policy attitudes, political efficacy seemed more relevant than typical measures of group efficacy (cf. Tausch et al., 2011, Study 3). 2) Because these policies relate to longstanding structural inequalities rather than a specific incident, efficacy to achieve the group's goals generally seemed more relevant than efficacy to address a specific issue (cf. Ufkes et al., 2015).

Perceived discrimination was measured using three items: "How much discrimination or unfair treatment do you think Asians face in the U.S.?", "How much discrimination or unfair treatment do you think people of color face in the U.S.?", and "How much discrimination or unfair treatment do you think you have faced in the U.S. because of your race or ethnicity?" ("None," "a little," "some," or "a lot" for each item.)

Finally, respondents were asked how much they agree or disagree (on a 5-point scale) with the following items: "Asians are socially and/or economically disadvantaged compared to Whites in the U.S."; "People of color are socially and/or economically disadvantaged compared to Whites in the U.S."; "I have less power than Whites do in the U.S."; "I have fewer opportunities than Whites do in the U.S."; "America is an open society where individuals of any ethnicity can achieve higher status"; and "Advancement in American society is possible for individuals of all ethnic groups." These items were drawn from a pool of similar items variously described as measuring inequality beliefs, power discontent, perceived illegitimacy, individual mobility beliefs, system blame, and system justification. See Appendix A for items.

Again, the order of these groups of items was randomized, and the item order within each group of items was also randomized.

Potential covariates. In addition to basic demographic questions (race, which I used as an additional screener, gender, education, and income), respondents were asked a series of questions about their ethnic and immigration background and a series of questions related to political sophistication and political orientation. The ethnic/immigration background questions included the respondent's self-identified ethnic group(s) (e.g., Chinese, Vietnamese, or Indian); whether the respondent is currently a U.S. citizen; whether the respondent was born in the U.S. and if not, in what year they came to live in the U.S.; and the respondent's preference for speaking English versus another language. The political questions included whether the respondent is registered to vote; whether the respondent voted in any past election in the U.S.; the respondent's self-identified ideology and party affiliation; and a 5-item political knowledge battery.

2. Results

Means and standard deviations for the key variables are presented in Table 1. When variables were measured with more than one item, the reported mean and standard deviation are for the composite score (i.e., the average of the item scores or, if the items are on different scales, the average of the 0-1 scaled item scores).

Table 1

Pilot Study Variable Means and Standard Deviations

	n	**Mean (SD)**
ID scale[a]		
Asian Am.	301	.693 (.225)
POC	301	.491 (.269)
American	301	.596 (.214)
ID rank		
Asian Am.	271	2.39 (1.15)
POC	271	4.06 (1.13)
American	271	3.35 (1.37)
ID checklist[b]		
Asian Am.	302	.560 (.497)
POC	302	.172 (.378)
American	302	.252 (.435)
Policy attitudes		
Immigration[c]	302	.628 (.216)
Criminal justice	302	.704 (.236)
Potential mediators		
Efficacy[d]	301	2.57 (0.72)
Group consciousness[e]	301	3.22 (0.69)

Note: Means and standard deviations are reported for composite scores (i.e., the average of the relevant item scores or, if the items are on different scales, the average of the 0-1 scaled item scores.

[a] Identity scale scores are on a 0-1 scale, with higher scores indicating greater identification with the group.
[b] Means on the identity checklist items reflect the proportion of respondents who checked that identity as important.
[c] Immigration and criminal justice composite scores are on a 0-1 scale, with higher scores indicating more liberal policy attitudes.
[d] Efficacy composite scores are on a 5-point scale, with higher scores indicating greater group-based political efficacy.
[e] Group consciousness composite scores consist of the linked fate, are on a 0-1 scale, with higher scores indicating higher group consciousness.

Identity measures. I expected the identity measures to load onto 3 correlated factors: Asian American identity, POC identity, and American identity. To test this, I used 4 confirmatory factor analysis models and modifications of those models and examined the fit statistics (CFI, RMSEA, and SRMR) for each model. Factor analysis was done using the lavaan package (Rosseel, 2012) in R. Model 1 included only the four items from the modified Huddy et al. (2015) scale for each identity. Model 2 included the scale items, as well as the ranks for each of the three identities of interest and an indicator variable for whether the respondent selected each of the three identities in the checklist. Model 3 included a scale composite score (generated by 0-1 scaling and then averaging the 4 scale items) for each identity and the rank and check variables from Model 2. Model 4 was similar to Model 2 but had the scale items for each identity loading onto a first-order factor, which then loaded onto a second-order factor with the rank and check variables for that identity. Models 2-4 were run with all observed variables treated as continuous, with the check variables treated as categorical, and with the rank and check items treated as categorical (ordered categorical in the case of the rank variables). For models with all variables treated as continuous, I used full-information maximum likelihood estimation (FIML); for models with categorical variables, I kept R's default settings, which use the WLSMV estimator with robust standard errors and list-wise deletion for missing observations.

If the initial model did not show adequate fit according to Hu and Bentler's (1999) criteria (CFI $\geq$ .95, RMSEA $\leq$ .06, SRMR $\leq$ .08), I examined modification indices. If indicated by the modification indices, I then added shared method covariances to the model (e.g., covariance between item 1 in the Asian American identity scale and item 1 in the POC identity scale).

Fit statistics and effective sample sizes are presented in Table 2. Model 1 initially did not meet the Hu and Bentler (1999) criteria for CFI (.908) or RMSEA (.116). Adding shared method covariances for each scale item across all 3 identities resulted in good fit based on CFI (.974) and SRMR (.043); RMSEA (.071) also improved but was still slightly above the Hu and Bentler criterion. Model 2 did not meet the fit criteria, with or without treating the rank and check variables as categorical and with or without shared method covariances. With categorical rank and check variables and shared method covariances for scale items, rank variables, and check variables, it came close to an adequate fit, at least based on non-robust fit statistics (CFI = .941, RMSEA = .074, SRMR = .088), but included an impossibly high correlation between the check variables for POC and American identities (r = 1.065). Model 3 with categorical rank and check variables and shared method covariances for scale composite scores, ranks, and check variables showed mostly adequate fit based on non-robust fit statistics (CFI = .974, RMSEA = .073, SRMR = .072) but also included an impossibly high correlation between the check variables for POC and American identities (r = 1.568). Similarly, Model 4 with categorical rank and check variables and shared method covariances for all items plus first-order factors fit according to all non-robust fit statistics and robust RMSEA (CFI = .992, non-robust RMSEA = .029, robust RMSEA = .057, SRMR = .066) but included an impossibly high correlation between the same two check variables (r = 1.560).

Table 2

Pilot Study Identity CFA Fit Statistics

	N	CFI	RMSEA	SRMR
Model 1 (Huddy scale only)				
no error covariances	301	.908	.116	.052
shared method covariances	301	.974	.071	.043
Model 2 (1st-order factors)				
continuous, no cov	302	.848	.104	.095
categorical rank & check, no cov	270	.885/.640	.096/.103	.113
categorical rank & check, shared method cov	270	.941/.785	.074/.085	.088
Model 3 (Huddy scale comp + rank & check				
continuous, no cov	302	.704	.162	.102
categorical rank & check, no cov	270	.843/.719	.141/.153	.147
categorical rank & check, shared method cov (rank & check)	270	.930/.859	.108/.126	.090
categorical rank & check, shared method cov (rank, check, & composite score)	270	.974/.939	.073/.090	.072
Model 4 (2nd-order factors)				
continuous, no cov	302	.864	.100	.111
categorical rank & check, no cov	270	.893/.681	.094/.098	.110
categorical rank & check, shared method cov (items)	270	.952/.822	.068/.079	.082
categorical rank & check, shared method cov (items + 1st-order factors)	270	.992/.909	.029/.057	.066

For comparison, measures of each identity had good internal consistency when only the Huddy et al. (2015) scale items were included (Asian American identity: α = .87; POC identity: α = .92; American identity: α = .86), but internal consistency decreased when the rank and check variables were included (Asian American identity: α = .64; POC identity: α = .74; American identity: α = .60). This decrease might be explained by lower correlations between item types than within the Huddy scale for each identity (Asian American identity: within r = .54-.69, between r = .29-.43; POC identity: within r = .67-.81, between r = .35-.54; American identity: within r = .55-.68, between r = .31-.43). Additionally, correlations across the three identities differed dramatically depending on the measure: For example, correlations among identities were positive for scales and checks but (not surprisingly) negative for ranks, and Asian American and POC identities had the highest correlation (r = .37) and POC and American identities had the lowest correlation (r = .09) for scale composite scores, but POC and American identities had the highest correlation for checks (r = .32) (see Table 3).

Table 3

Pilot Study Correlations among Asian American, POC, and American Identities

	Asian American	Person of color	American
Huddy scale[a]			
Asian American	1.000		
Person of color	.372	1.000	
American	.122	.088	1.000
Ranks[b]			
Asian American	1.000		
Person of color	-.038	1.000	
American	-.213	-.408	1.000
Checklist			
Asian American	1.000		
Person of color	.210	1.000	
American	.023	.322	1.000

[a] Correlations among composite scores for each identity. (Composite scores were generated by 0-1 scaling items and then averaging responses for each identity.)
[b] Correlations for ranks are Spearman correlations. All other correlations are Pearson correlations.

These results provide evidence for a 3-factor structure but suggest that the Huddy et al. (2015) scale, rankings, and checklist might measure identity distinctly enough to make it difficult to consolidate the measures into a single meaningful score for each identity.

Policy attitude measures. A 2-factor oblique CFA model was tested for the policy attitude items, with the 3 immigration items on one factor and the 3 criminal justice items on the other factor.[2] Fit was not ideal initially (CFI = .942, RMSEA = .118, SRMR = .044), though the 2-factor model fit better than a 1-factor model (CFI = .895, RMSEA = .149, SRMR = .059). Modification indices suggested adding a parameter for the error covariance between the number of people in prison item and the mandatory minimum sentence item; adding this error covariance produced a model with good fit (CFI = .988, RMSEA = .056, SRMR = .020). The correlation between the two factors was high (*r* = .82), and internal consistency for the two groups of policy items (after 0-1 coding all items) was lower than ideal (immigration α = .76, criminal justice α = .72). Nonetheless, the CFA suggests that these items capture two distinct policy areas as intended.

Potential mediators. Exploratory factor analysis was done using the nFactors package (Rache & Magis, 2020) in R. Although the pool of potential mediator items produced 3 eigenvalues greater than 1, parallel analysis suggested a 2-factor solution, and the scree plot showed large drops after the first and second eigenvalues but not subsequent ones. One, 2-, and 3-factor oblique solutions were examined. The 2-factor solution, with the efficacy items loading on one factor and most of the remaining items loading primarily on the other, appeared to be the most readily interpretable. However, two items (“America is an open society where individuals of any ethnicity can achieve higher status” and “Advancement in American society is possible for individuals of all ethnic groups”) did not clearly load on either factor over the other, and these two items

[2] The number of people in prison item was treated as continuous for the purpose of the pilot study CFAs. In Study 1, I fit alternative models treating this item as ordered categorical.

formed their own factor in the 3-factor solution. EFA was repeated with the addition of an item measuring concern about discrimination due to COVID-19, and the results did not change substantially; the COVID discrimination item loaded onto the same factor as the linked fate, perceived discrimination, and miscellaneous disadvantage/deprivation items. Factor loadings for the 2-factor solution, with and without the COVID discrimination item, are displayed in Table 4.

Table 4

Pilot Study Mediator Item Factor Loadings for 2-factor Solution

	without COVID item		**with COVID item**	
	Factor 1	*Factor 2*	*Factor 1*	*Factor 2*
asianLF	.700	.129	.718	.125
pocLF	.689	.163	.698	.154
pd_asian	.697	.157	.711	.150
pd_poc	.654	-.008	.635	-.033
pd_self	.690	.156	.713	.155
misc1	.715	-.111	.713	-.127
misc2	.653	-.140	.629	-.166
misc3	.714	-.150	.704	-.169
misc4	.780	-.102	.766	-.125
misc5r	.360	-.364	.341	-.379
misc6r	.294	-.398	.287	-.405
covid			.529	.091
effasian1	-.206	.552	-.184	.565
effasian2	.052	.769	.064	.759
effpoc1	-.100	.490	-.090	.493
effpoc2	.156	.644	.158	.626

Note: Factor correlation r = -.098 without COVID discrimination concern item; r = -.103 with COVID discrimination concern item.

Based on the EFA, the two items that did not clearly load onto either factor in the 2-factor solution were dropped for Study 1. This left 4 efficacy items (α = .73) and 10 items related to group-based injustice or inequality (α = .89) (2 linked fate, 3 perceived discrimination, 5 miscellaneous disadvantage/deprivation). I hypothesized that a 2-factor model would adequately fit the data on these items in Study 1.

Potential covariates. Potential covariates were examined for whether they predicted the identity, policy attitude, and potential mediator items in ordinary least-squares multiple regression analyses, with the idea of dropping items for Study 1 if they did not predict any of the key variables. To simplify the analyses with the ethnicity variable, dummy variables were created for whether a respondent identified as East Asian (Chinese, Korean, Japanese, or Taiwanese) and whether a respondent identified as South Asian (Indian, Pakistani, or Bangladeshi). The ethnicity variables, nativity (1 = foreign-born) or age of arrival in the U.S., language preference, gender (male = 1; 0 otherwise), age, income, and political ideology each predicted at least one identity; political ideology or party, political knowledge, past vote, gender, age, and education each predicted policy attitudes in at least one area; language preference, age of arrival in the U.S., and political ideology predicted a composite of the non-efficacy mediator factor; and ethnicity and political knowledge predicted efficacy. These analyses suggested that voter registration could be dropped, as it did not significantly predict any of the variables of interest. Additionally, although political knowledge predicted criminal justice attitudes and efficacy, political knowledge scores in this sample were extremely high (median = 4 out of 5 questions correct), suggesting that political knowledge effects among Asian American respondents recruited through Prolific might not be representative of effects across the entire range of political knowledge among Asian American adults. This observation, along with the length of the political knowledge battery, led me to drop political knowledge as a potential covariate in Study 1.

B. Study 1 Method

Respondents

Respondents were 1006 Asian Americans recruited through Prolific. The target number of respondents for Wave 1 was determined based on power analyses for RI-CLPM[3], using Monte Carlo simulation in Mplus (Muthén & Muthén, 1998-2019; Muthén & Muthén, 2002), and a 25% attrition rate across successive waves. The attrition estimate was based on Prolific's estimate of less than 25% over a year, https://researcher-help.prolific.co/hc/en-gb/articles/360009223613-Minimising-dropout-attrition-rate-in-longitudinal-studies, as well as reported retention rates in published studies using Prolific that ranged from 57% over 2 months (Maertens et al., 2021) to 85.8% over 2 weeks around the 2016 election (Zucker, Weis, & Richman, 2019; see also Kadhim, Amiot, & Louis, 2020; Palan & Schitter, 2018; Maher, MacCarron, & Quayle, 2020; Gordon-Hacker & Gueron-Sela, 2020; Costin & Vignoles, 2020, Study 3). Power analyses indicated that between 500 and 600 respondents would be needed to detect a cross-lagged effect of $\beta = 0.2$ with approximately power = .80. To have that number of respondents complete all three waves with 25% attrition across successive waves would require N = 667-800 in Wave 2 and N = 890-1067 in Wave 1.

Respondents were identified using the same filters as for the pilot study (ethnicity = Asian, nationality = United States), with the additional criterion that respondents from

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[3] Because the CLPM is nested under the RI-CLPM and has fewer parameters to estimate (Hamaker et al., 2015), it does not require as large of a sample as the RI-CLPM. I also did power analyses for detecting *a*, *b*, and *ab* effects in longitudinal mediation models, as described in Appendix B, and those analyses indicated a somewhat smaller target sample size than the RI-CLPM power analyses did. Therefore, target sample size estimates were based on the RI-CLPM power analyses.

the pilot study were not eligible for this study. Respondents who did not self-identify as Asian or Asian American were excluded from Waves 2 and 3 and from further analysis, except for one respondent who marked Other and wrote “Southeast Asian.” After removing 10 respondents who did not identify as Asian or Asian American, 7 respondents who did not answer the race question, and 1 respondent who appeared to be under 18, the final sample size in Wave 1 was 988.

Most respondents self-identified only as Asian or Asian American, but 21 also identified as White, 6 also identified as Hispanic/Latino, 6 also identified as Native Hawaiian or Pacific Islander, 1 also identified as Black, and 1 also identified as “Mixed.” As in the pilot study, the most common ethnic subgroups were Chinese (N = 409), Vietnamese (N = 155), Indian (N = 113), Filipino (N = 109), and Korean (N = 106). Again, as in the pilot study, most respondents were U.S. citizens (965 citizens, 23 non-citizens), and the majority (764, or 77%) were born in the U.S. Respondents were relatively balanced on gender (488 male, 480 female, 20 nonbinary). Although respondents’ ages ranged from 18-72, they tended to be relatively young (Mean = 26.8, SD = 8.3). They also tended to be well-educated (592, or 60%, had at least a 4-year college degree) and have relatively high incomes (median = $70,000-79,000; mode = $100,000-149,000).

The study was administered in 3 waves: Wave 1 ran from November 9 to November 11, 2020, Wave 2 ran from November 30 to December 4, 2020, and Wave 3 ran from December 28, 2020, to January 2, 2021. Attrition rates were around 20% (20% between Waves 1 and 2; 17% between Waves 2 and 3), leaving a sample size of N = 787 for Wave 2 and N = 651 for Wave 3. Thus, the sample size of respondents who completed all three waves should have been adequate to detect effects across model types.

Materials and Procedure

Survey items consisted of 1) the identity items from the pilot study; 2) racial attitude measures; 3) measures of attitudes in three different policy areas: immigration, criminal justice reform, and affirmative action; 4) the potential mediator items from the pilot study except the two items that formed a third factor; and 5) the COVID discrimination concern item from the pilot study. Wave 1 also included the potential covariates from the pilot study except the voter registration and political knowledge items.

Racial attitude measures. I used two types of explicit racial attitude measures, feeling thermometers (FTs) and so-called stereotype items (see, e.g., Sears et al., 1997), to capture attitudes toward Whites, Blacks, and Latinos. Feeling thermometer items ask respondents to rate their feelings toward people or groups on a 100-point sliding scale with 1 = coldest/most negative and 100 = warmest/most positive. Stereotype items ask respondents to rate a group on a 7-point scale anchored on two opposite traits (e.g., 1 = lazy, 7 = hardworking). Respondents in this study were asked to rate each group on the following pairs of traits: lazy-hardworking and unintelligent-intelligent. (These pairs of traits were used in the 2016 CSPP study and the American National Election Studies (ANES) 2016 Time Series Study.) Higher ratings on the FTs and stereotype items indicate more positive attitudes toward the target group.

Policy attitude/support for change measures. Attitudes toward immigration and criminal justice reform were measured using the six items from the pilot study (3 for immigration, 3 for criminal justice reform). Attitudes toward affirmative action were measured using two items: one measuring the extent to which respondents favor affirmative action in employment and one measuring the extent to which respondents favor affirmative action in higher education (5-point scales; 1 = strongly oppose, 5 = strongly favor). See Appendix A for items. Before analysis, items were recoded so that higher scores represent positions that favor racial minorities (i.e., more liberal immigration policies or more support for criminal justice reform or affirmative action).

All items except the potential covariates were included in all 3 waves. The order of the different types of items (identity, racial attitudes, policy attitudes, linked fate, political efficacy, perceived discrimination) was counterbalanced within each wave. The order of the identities (i.e., race, POC, American) for the identity, linked fate, and efficacy items, and the order of the racial attitude (FTs vs. stereotypes) and policy items were randomized, as was the group order for the racial attitude items. To avoid priming racial identity, the demographic items were asked at the end of the Wave 1 survey.

Dummy variables were created for East Asian and South Asian ethnic groups, nativity (1 = foreign-born; 0 otherwise), gender (1 = male; 0 otherwise), and past vote (1 = voted in a past election in the U.S.; 0 otherwise). Political party affiliation was collapsed into a 7-point scale (1 = strong Democrat, 2 = not strong Democrat, 3 = lean Democratic, 4 = Independent, 5 = lean Republican, 6 = not strong Republican, 7 = strong Republican). These variables, as well as age, income, education, age of arrival in the U.S., language preference (with higher numbers indicating preference for English compared to another language) and political ideology were included as covariates in CLPM models.

To facilitate comparison of effects, I recoded all items to range from 0 to 1. Where warranted by longitudinal confirmatory factor analysis, I created factor scores to consolidate items. Because White stereotypes and affirmative action attitudes were each represented by only two items at each time point that were highly correlated, instead of creating factor scores, I averaged the two items for each construct at each time point.

C. Results

1. Descriptive Statistics

Means and standard deviations in each wave for the key variables are presented in Table 5.

Table 5

Study 1 Variable Means and Standard Deviations

	Wave 1		**Wave 2**		**Wave 3**	
	n	*Mean (SD)*	*n*	*Mean (SD)*	*n*	*Mean (SD)*
ID scale[a]						
Asian Am.	988	.719 (.201)	786	.707 (.200)	650	.701 (.201)
POC	988	.501 (.263)	786	.504 (.260)	650	.490 (.261)
American	988	.606 (.207)	786	.596 (.208)	650	.589 (.208)
ID rank						
Asian Am.	978	2.39 (1.10)	769	2.50 (1.07)	635	2.55 (1.08)
POC	978	4.03 (1.14)	769	4.10 (1.10)	635	4.16 (1.07)
American	978	3.49 (1.30)	769	3.52 (1.30)	635	3.59 (1.26)
ID checklist[b]						
Asian Am.	986	.663 (.473)	785	.608 (.489)	650	.592 (.492)
POC	986	.267 (.442)	785	.250 (.431)	650	.228 (.420)
American	986	.398 (.490)	785	.360 (.480)	650	.358 (.480)
Racial attitudes						
Nonwhite FT	988	65.3 (19.8)	783	65.0 (19.9)	651	64.5 (19.7)
White FT	984	57.9 (21.0)	780	58.3 (21.7)	649	57.8 (21.7)
Nonwhite stereotypes	988	4.93 (1.11)	785	4.88 (1.12)	650	4.83 (1.09)
White stereotypes	988	4.53 (1.10)	785	4.53 (1.11)	650	4.50 (1.10)
Policy attitudes						
Immigration[c]	988	.647 (.208)	786	.650 (.207)	651	.645 (.201)

Criminal justice	988	.732 (.218)	787	.735 (.221)	651	.739 (.226)
Affirmative action[d]	988	2.92 (1.10)	787	3.02 (1.10)	651	3.02 (1.11)
Potential mediators[e]						
Efficacy	988	2.63 (0.64)	784	2.55 (0.63)	650	2.53 (0.62)
Linked fate	929	2.75 (0.91)	734	2.75 (0.92)	608	2.72 (0.89)
Perceived discrimination	988	3.02 (0.58)	784	3.01 (0.57)	650	2.96 (0.57)
Relative deprivation	988	3.77 (0.81)	784	3.80 (0.79)	650	3.82 (0.77)

Note: Means and standard deviations are reported for composite scores. Further analyses involve factor scores for the identity scales, nonwhite racial attitude measures, immigration and criminal justice policy attitude measures, and mediator measures.

[a] Identity scale scores are on a 0-1 scale, with higher scores indicating greater identification with the group.
[b] Means on the identity checklist items reflect the proportion of respondents who checked that identity as important.
[c] Immigration and criminal justice composite scores are on a 0-1 scale, with higher scores indicating more liberal policy attitudes.
[d] Affirmative action composite scores are on a 5-point scale, with higher scores indicating more support for/less opposition to affirmative action.
[e] Efficacy composite scores are on a 5-point scale, with higher scores indicating greater group-based political efficacy. Linked fate is on a 4-point scale (1 = no linked fate; 2 = not very much; 3 = some; 4 = a lot). Perceived discrimination composite scores are on a 4-point scale, with higher scores indicating more perceived discrimination. Relative deprivation composite scores are on a 5-point scale with higher scores indicating greater relative deprivation.

Notably, across identity measures, respondents appeared to identify relatively strongly as Asian American (mean scale and checklist scores above the midpoint, mean rankings below the midpoint) but less strongly as POC or American. Identification seemed particularly weak for POC identity, which only around a quarter of respondents checked as important in each wave (compared to somewhat over a third of respondents checking American identity and nearly two-thirds of respondents checking Asian American identity) and which was the only identity for which mean Huddy scale composite scores were not consistently above the midpoint. As in the pilot study, correlations among the three identities varied depending on how identity was measured (see Table 6). With the Huddy scale factor scores, correlations were highest between Asian American and POC identities (*r* = .40-.47), and POC and American identities were practically uncorrelated (*r* = -.03-.004). A similar pattern emerged for the checklist, but the difference between the highest and lowest correlations was smaller. POC and American identities had the strongest (negative) correlation for ranks (*r* = -.45 to -.57).

Table 6

Study 1 Identity Intercorrelations

	Asian American ID	**POC ID**	**American ID**
Identity scale factor scores W1			
Asian American identity	1.000		
POC identity	.453	1.000	
American identity	.277	-.026	1.000
Identity scale factor scores W2			
Asian American identity	1.000		
POC identity	.469	1.000	
American identity	.277	-.009	1.000
Identity scale factor scores W3			
Asian American identity	1.000		
POC identity	.397	1.000	
American identity	.278	.004	1.000
Identity ranks W1			
Asian American identity	1.000		
POC identity	-.040	1.000	
American identity	-.127	-.453	
Identity ranks W2			
Asian American identity	1.000		
POC identity	.024	1.000	
American identity	-.188	-.491	1.000
Identity ranks W3			
Asian American identity	1.000		
POC identity	.023	1.000	
American identity	-.195	-.567	1.000
Identity checklist W1			

Asian American identity	1.000		
POC identity	.255	1.000	
American identity	.145	.161	1.000
Identity checklist W2			
Asian American identity	1.000		
POC identity	.259	1.000	
American identity	.109	.095	1.000
Identity checklist W3			
Asian American identity	1.000		
POC identity	.264	1.000	
American identity	.183	.114	1.000

Mean racial attitude scores were above the midpoint for both White and nonwhite target groups on both feeling thermometers and stereotype scales, though the means for nonwhite FT and stereotype ratings appear slightly higher than those for White FT and stereotype ratings. Respondents' policy positions were, on average, on the side of benefitting the relevant minority group or groups with regard to immigration and criminal justice reform (means > .5, the midpoint of a 0-1 scale). However, mean responses were around the midpoint between favoring and opposing affirmative action.

Stability of Measures. Because one of the major differences between CLPM and RI-CLPM is their assumptions about variable stability (Orth et al., 2021), I examined the correlations of each variable (generally factor scores or composite scores except for the White FT) with itself across the three waves of the study. These correlations are presented in Table 7. As one might expect, the identity scale factor scores (r = .82-.93) and racial attitude variables (r = .60-.83) show high levels of stability over the time frame of this study. Surprisingly, the policy attitude variables, especially the immigration and criminal justice factor scores (r = .97-.999), show as much or more stability. These high levels of stability potentially underlie some of the model convergence issues discussed below in the results for identity and policy attitudes.

Table 7

Study 1 Variable Autocorrelations

	W1-W2	**W2-W3**	**W1-W3**
Identity scale factor scores			
Asian American ID	.822	.876	.816
POC ID	.894	.893	.864
American ID	.919	.928	.914
Identity ranks (Spearman correlations)			
Asian American ID	.478	.577	.502
POC ID	.547	.657	.566
American ID	.646	.668	.612
Identity checklist			
Asian American ID	.435	.513	.492
POC ID	.536	.623	.536
American ID	.472	.563	.437
Racial attitude variables			
Non-White FT factor score	.809	.832	.755
Non-White stereotype factor score	.712	.765	.767
White FT	.752	.772	.756
White stereotype composite	.627	.671	.600
Policy attitude variables			
Immigration factor score	.990	.992	.999
Criminal justice factor score (continuous indicators)	.972	.975	.966
Criminal justice factor score (categorical indicator)	.992	.992	.989
Affirmative action composite	.797	.843	.816
Potential mediators			
Efficacy factor score	.784	.780	.862
Linked fate factor score	.803	.894	.820
Perceived discrimination factor score	.856	.819	.735
Relative deprivation factor score	.875	.894	.877

2. Confirmatory Factor Analysis

Confirmatory factor analysis was done for the identity, racial attitude, policy attitude, and mediator items both cross-sectionally within each wave and longitudinally. All CFAs were done using the lavaan package (Rosseel, 2012) in R. Cross-sectional CFAs used lavaan's default settings: list-wise deletion for missing data, maximum likelihood estimation for models with continuous indicators, and WLSMV estimator with robust standard errors for models with categorical indicators. Longitudinal CFAs were initially run with full-information maximum likelihood estimation if all indicators were continuous or diagonally weighted least squares estimation with pairwise deletion and robust standard errors (from the WLSMV estimator) if any indicators were treated as categorical. However, this estimation method imputed factor scores for missing data, which seemed inappropriate for a longitudinal study with attrition, and some initial panel models using factor scores generated from these models failed to converge. Thus, the CFAs were re-run with list-wise deletion. In all longitudinal CFA models, residual covariances were allowed for each observed variable with itself across waves. Longitudinal models were used to test equality of factor loadings and then intercepts across waves, and factor scores for identity, attitudes toward nonwhites, immigration and criminal justice attitudes, and potential mediators were generated based on the most stringent model that did not significantly worsen model fit.

Identity. I expected a 3-factor model with the three identities (Asian American, POC, and American) as factors to fit the data in each wave. Cross-sectional CFA fit statistics are presented in Table 8. In each wave, a 3-factor model with only the Huddy scale items for each identity and shared method error covariances fit well based on CFI (.981-.982), RMSEA (.056-.057), and SRMR (.033-.044). First-order factor models with the scale items, ranks, and checks did not fit well: SRMR indicated good fit only for Wave 1 with shared method error covariances and check variables treated as categorical (SRMR = .078); CFI and RMSEA never met fit criteria. Models with Huddy scale composite scores and rank and check variables met the fit criteria for SRMR (.063-.069) and CFI based on non-robust estimates (.954-.979) when shared method error covariances were included, but they did not meet fit criteria for RMSEA (non-robust RMSEA = .079-.093). Second-order factor models with shared method error covariances for ranks, checks, and first-order scale factors mostly fit well based on non-robust fit statistics (CFI = .961-.971; RMSEA = .056-.062; SRMR = .063-.068) but not robust CFI (.836-.872) or robust RMSEA (.069-.074).

Table 8

Study 1 Identity Cross-sectional CFA Fit Statistics

	Wave 1				Wave 2				Wave 3			
	N	*CFI*	*RMSEA*	*SRMR*	*N*	*CFI*	*RMSEA*	*SRMR*	*N*	*CFI*	*RMSEA*	*SRMR*
Model 1 (Huddy scale only)	973				780				644			
no error covariances		.916	.105	.048		.903	.114	.059		.889	.126	.055
shared method covariances		.981	.057	.033		.982	.056	.044		.982	.057	.034
Model 2 (1st-order factors)	963				763				629			
categorical rank & check, no cov		.878/ .631	.107/ .112	.103		.851/ .550	.122/ .126	.115		.843/ .520	.131/ .134	.121
categorical check, no cov		.890/ .667	.094/ .099	.098		.869/ .600	.105/ .109	.109		.870/ .584	.107/ .111	.112
categorical rank & check, shared method cov		.929/ .770	.088/ .095	.081		.911/ .711	.101/ .109	.092		.919/ .723	.101/ .109	.092
categorical check, shared method cov		.932/ .778	.080/ .087	.078		.915/ .719	.091/ .098	.088		.921/ .723	.089/ .098	.087
Model 3 (Huddy scale comp + rank & check)	976				769				635			
categorical rank & check, no cov		.850/ .720	.150/ .168	.134		.888/ .776	.142/ .160	.126		.890/ .772	.154/ .174	.138
categorical check, no cov		.802/ .591	.146/ .169	.131		.838/ .642	.140/ .164	.124		.828/ .600	.148/ .176	.134
categorical rank & check, shared method cov		.964/ .927	.093/ .108	.069		.976/ .946	.083/ .099	.063		.979/ .949	.086/ .104	.066
categorical check, shared method cov		.954/ .897	.089/ .107	.067		.968/ .919	.079/ .098	.063		.968/ .915	.080/ .103	.063
Model 4 (2nd-order factors)	963				763				629			

categorical rank & check, no cov	.881/ .645	.106/ .111	.103	.864/ .632	.118/ .115	.115	.870/ .658	.120/ .114	.119
categorical check, no cov	.891/ .676	.095/ .099	.099	.870/ .616	.106/ .108	.111	.870/ .574	.108/ .114	.112
categorical rank & check, 1st-order factor cov	.946/ .805	.073/ .084	.084	.950/ .815	.072/ .083	.084	.951/ .807	.075/ .087	.090
categorical check, 1st-order factor cov	.942/ .779	.070/ .083	.082	.945/ .782	.069/ .082	.082	.946/ .767	.070/ .085	.086
categorical rank & check, shared method cov (r&c + 1st-order factors)	.967/ .871	.058/ .070	.064	.965/ .860	.062/ .074	.068	.971/ .872	.059/ .072	.068
categorical check, shared method cov (r&c + 1st-order factors)	.965/ .854	.056/ .069	.063	.961/ .836	.060/ .073	.067	.967/ .842	.056/ .072	.067

Longitudinal CFA only showed adequate fit for models with the Huddy scale items alone and within-wave shared method error covariances (unconstrained model CFI = .957, RMSEA = .050, SRMR = .051). Furthermore, models with rank and check variables, especially if they included shared method error covariances, tended to produce warnings about covariance matrices that were not positive definite, negative residual variances, or both. Fit statistics for all longitudinal CFA models with list-wise deletion are presented in Table 9. As was true in the pilot study, identity scale internal consistency was higher with only the Huddy scale items (Asian American: W1 & W2 $\alpha = .84$, W3 $\alpha = .85$; POC: W1 & W2 $\alpha = .91$, W3 $\alpha = .92$; American: $\alpha = .84$ in all 3 waves) than with those items and the ranks and checks (Asian American: W1 $\alpha = .77$, W2 $\alpha = .79$, W3 $\alpha = .80$; POC: $\alpha = .88$ in all 3 waves; American: W1 & W2 $\alpha = .80$, W3 $\alpha = .81$). This pattern, along with the longitudinal CFA results, again suggests that the different measures of identity might capture slightly different constructs. Accordingly, the panel models I report below use identity factor scores based on the longitudinal CFA with only the Huddy scale items and within-wave shared method error covariances.

For this longitudinal CFA model, constraining factor loadings to be equal across waves did not significantly affect fit (constrained: $\chi^2_{504} = 1276.345$, unconstrained: $\chi^2_{486} = 1265.408$, $\Delta\chi^2_{18} = 10.937$, $p = .897$). But subsequently constraining intercepts to be equal across waves resulted in significantly worse fit (constrained: $\chi^2_{528} = 1328.846$, unconstrained: $\chi^2_{504} = 1276.345$, $\Delta\chi^2_{24} = 52.501$, $p < .001$). Thus, factor scores for each identity (Asian American, POC, and American) were generated from the model with equal loadings. The standardized version of the final longitudinal CFA model used to generate identity factor scores is presented in Figure 5, with residual variances, item residual covariances, and cross-identity cross-wave covariances omitted for readability.

Table 9

Study 1 Identity Longitudinal CFA Fit Statistics

		N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
Model 1 (Huddy scale only)		632					
no within-wave error covariances			.936	.059	.053	1681.674 (522)	
within-wave shared method covariances	*unconstrained*		.957	.050	.051	1265.408 (486)	
	=loadings		.957	.049	.051	1276.345 (504)	10.937 (18)
	=intercepts		.956	.049	.050	1328.846 (528)	52.501 (24)***
Model 2 (1st-order factors)		603					
no w/in wave error cov, categorical rank & check			.904/ .619	.098/ .075	.102	8767.836/ 5688.259 (1287)	
no w/in wave error cov, categorical check			.909/ .627	.086/ .067	.097	6969.178/ 4744.379 (1287)	
rank & check cov w/in wave, categorical rank & check			.916/ .658	.092/ .072	.097	7779.116/ 5215.211 (1269)	
rank & check cov w/in wave, categorical check[a]			.916/ .651	.083/ .065	.093	6471.418/ 4503.303 (1269)	
all shared method cov w/in wave, categorical rank & check[a]			.924/ .684	.089/ .070	.093	7154.435/ 4886.139 (1233)	
all shared method cov w/in wave, categorical check			.924/ .676	.080/ .064	.089	5940.223/ 4230.469 (1233)	
Model 3 (Huddy scale comp + rank & check)		618					
no w/in wave error cov, categorical rank & check[b]			.936/ .825	.114/ .103	.117	2350.749/ 1976.728 (261)	

no w/in wave error cov, categorical check[a]		.903/ .700	.110/ .104	.113	2195.332/ 2006.116 (261)
w/in-wave shared method covariances, categorical rank & check[a,d]		.960/ .879	.095/ .091	.093	1547.685/ 1420.363 (234)
w/in-wave shared method covariances, categorical check[a,d]		.940/ .797	.091/ .090	.091	1428.733/ 1414.966 (234)
Model 4 (2nd-order factors)	603				
no w/in wave error cov, categorical rank & check[c]		.905/ .629	.098/ .075	.102	8616.024/ 5564.223 (1278)
no w/in wave error cov, categorical check[c]		.909/ .627	.068/ .067	.097	6940.147/ 4737.329 (1278)
1st order factor cov w/in wave, categorical rank & check[d]		.928/ .693	.085/ .068	.095	6841.676/ 4816.870 (1269)
1st order factor cov w/in wave, categorical check[b]		.928/ .674	.077/ .063	.090	5746.573/ 4288.816 (1269)
1st order factor & r&c cov w/in wave, categorical rank & check[d]		.936/ .720	.081/ .066	.088	6225.491/ 4492.432 (1253)
1st order factor & r&c cov w/in wave, categorical check[a,c]		.935/ .700	.073/ .061	.085	5302.426/ 4029.681 (1253)

Note: Models with first-order factor error correlations had impossible correlations among first-order factors (within-wave) and between the Wave 2 and 3 American identity second-order factors. In some models with rank and check covariances, some within-wave check covariances were impossible.

Note: χ^2 was significant for all models at the $p < .001$ level. To save space, significance indicators are omitted for the χ^2 column.

[a] Model converged with a warning that the covariance matrix of the residuals of the observed variables was not positive definite.
[b] Negative residual variance (and corresponding impossible loading) for American identity rank
[c] Negative residual variance (and corresponding impossible loading onto the second-order factor) for 1st-order Asian American identity scale factor in Wave 3 and/or Wave 1

[d] Model converged with a warning that the covariance matrix of latent variables was not positive definite.

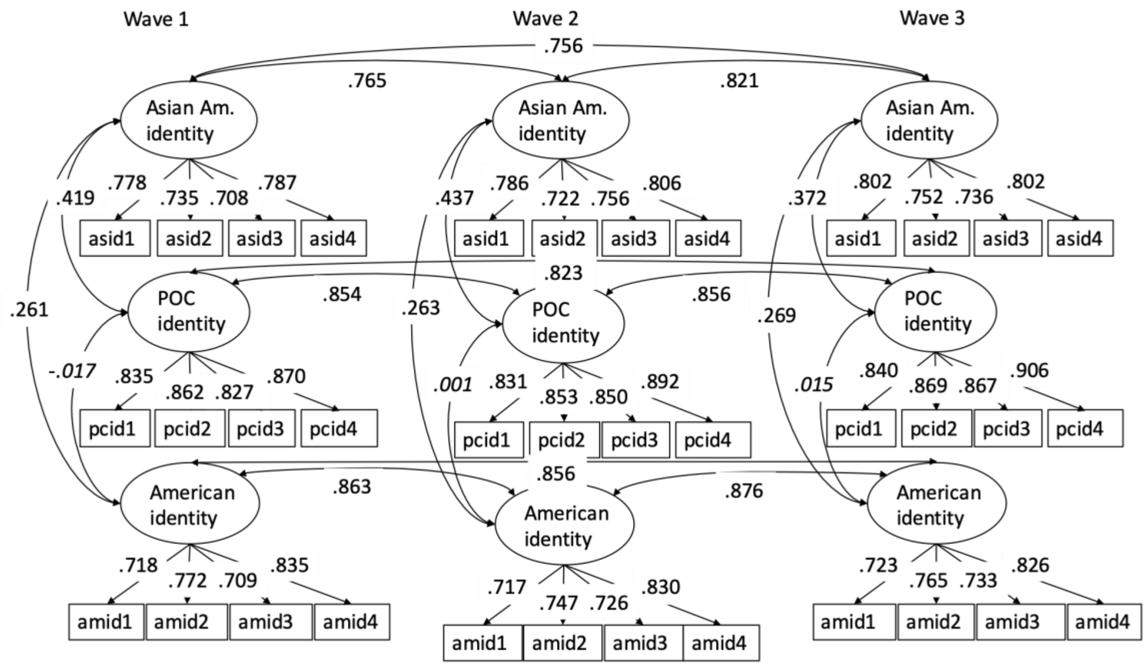


Figure 5. Study 1 identity final 3-factor longitudinal CFA model, showing standardized coefficients. This model includes only the Huddy scale items for each identity, with item residual autocorrelations across waves, within-wave shared method covariances for each scale item across identities, and equal (unstandardized) factor loadings across waves. Item residual covariances and cross-identity, cross-wave factor covariances are omitted from the figure for readability. Italics indicate non-significant within-wave factor correlations (between POC and American identities).

Racial attitudes. Cross-sectional CFA models with all items about nonwhites loading onto a single factor and no error covariances did not fit well in any wave (CFI = .759-.762; RMSEA = .355-.362; SRMR = .088-.094). Adding shared method covariances (i.e., between the FTs and between the same stereotype item for the different target groups) resulted in adequate fit based on SRMR (.029-.041) and based on CFI in Wave 1 (.963), but RMSEA remained high across waves (.171-.215). For comparison, a 1-factor model for nonwhite stereotypes (with no error covariances) showed good fit based on CFI (.955-.969) and SRMR (.029-.036) but again, not based on RMSEA (.205-.244). Fit statistics are presented in Table 10. (Cross-sectional CFA models could not be tested for the White FT and stereotype items because they would have been just-identified.) Black and Hispanic/Latino FT ratings were highly correlated in each wave (W1 $r = .866$, W2 $r = .867$, W3 $r = .863$), and internal consistency for a scale combining the Black and Hispanic stereotype items was high ($\alpha = .89$ in every wave), though dropping the Hispanic lazy-hardworking item tended to increase alpha.

Table 10

Study 1 Racial Attitude Cross-sectional CFA Fit Statistics

	Wave 1				**Wave 2**				**Wave 3**			
	N	*CFI*	*RMSEA*	*SRMR*	*N*	*CFI*	*RMSEA*	*SRMR*	*N*	*CFI*	*RMSEA*	*SRMR*
Attitudes toward non-Whites, 1 factor	984				781				646			
no error covariances		.761	.355	.094		.759	.362	.092		.762	.355	.088
FT cov		.949	.174	.033		.938	.195	.037		.938	.192	.037
shared method cov		.963	.171	.029		.944	.215	.038		.942	.215	.041
Non-White stereotypes	984	.962	.228	.033	783	.969	.205	.029	646	.955	.244	.036

Longitudinal CFA with full-information maximum likelihood estimation similarly showed that a 1-factor model of attitudes toward nonwhites did not fit (CFI = .806, RMSEA = .162, SRMR = .133). A 2-factor model with the feeling thermometers on one factor and the stereotype items on the other factor fit well based on CFI (.962) and SRMR (.033), but RMSEA (.076) was somewhat higher than ideal. Constraining loadings and intercepts to be equal across waves did not significantly affect model fit. However, with list-wise deletion and regular maximum likelihood estimation, the 2-factor model had an impossible residual covariance for one of the feeling thermometer items between Wave 1 and Wave 3. Thus, I also modeled nonwhite FTs and nonwhite stereotypes separately. The nonwhite stereotypes model fit well based on CFI (.972) and SRMR (.043) but not RMSEA (.089). Constraining loadings to be equal across waves did not significantly affect model fit ($\chi^2_{45} = 241.409$, $\chi^2_{39} = 236.354$, $\Delta\chi^2_5 = 5.066, p = .535$), and neither did constraining intercepts to be equal across waves ($\chi^2_{53} = 248.986, \Delta\chi^2_8 = 7.577, p = .476$). The nonwhite FT unconstrained model was just identified; however, despite warnings that the smallest eigenvalues were close to 0, the equal loadings and equal intercepts models fit well (equal loadings: CFI = 1.000, RMSEA = .005, SRMR = .004, $\chi^2_2 = 2.029$; equal intercepts: CFI = .999, RMSEA = .030, SRMR = .009, $\chi^2_6 = 9.530$), and neither constraint significantly affected fit (equal loadings: $\Delta\chi^2_2 = 0.321, p = .852$; $\Delta\chi^2_4 = 7.501, p = .112$). Fit statistics for longitudinal models of attitudes toward nonwhites are presented in Table 11. Because of the problems with the 2-factor model, factor scores for nonwhite stereotypes and FTs were generated from the separate FT and stereotype models with equal intercepts. Standardized versions of the final models used to generate factor scores are presented in Figure 6.

Table 11

Study 1 Racial Attitude Longitudinal CFA Fit Statistics

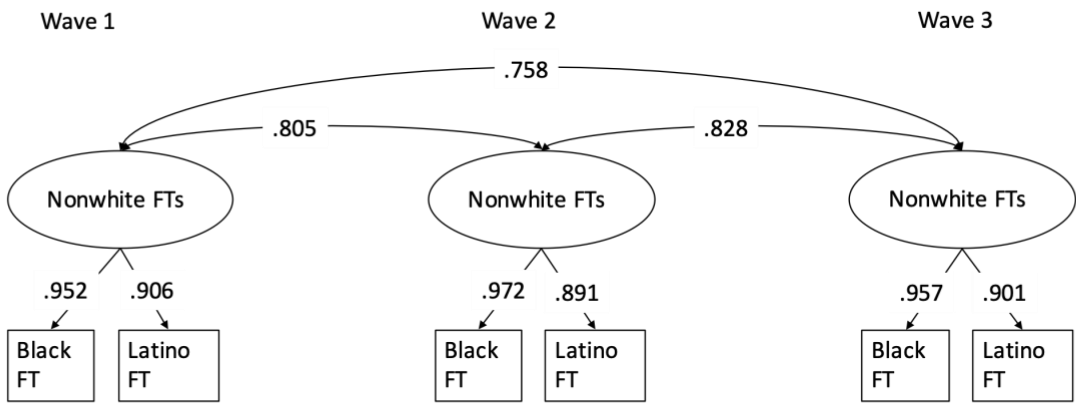
		N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
Attitude toward non-Whites, 1 factor (FIML)		988	.806	.162	.133	3058.534 (114)	
Attitude toward non-Whites, 2 factor (FIML)	*unconstrained*	988	.962	.076	.033	677.977 (102)	
	=loadings		.962	.073	.036	685.075 (110)	7.098 (8)
	=intercepts		.962	.069	.037	702.179 (122)	17.104 (12)
Attitude toward non-Whites, 2 factor (no FIML)	*unconstrained*[a]	642	.963	.084	.039	565.695 (102)	
	=loadings[a]		.963	.081	.041	571.756 (110)	6.061 (8)
	=intercepts[a]		.963	.077	.039	584.028 (122)	12.272 (12)
Attitudes toward Whites (FIML)	*unconstrained*	988	.971	.096	.088	150.214 (15)	
	=loadings		.971	.085	.089	154.242 (19)	4.028 (4)
	=intercepts		.971	.074	.089	159.565 (25)	5.323 (6)
Non-White FTs (no FIML)	*unconstrained*[b]	650	1.000	.000	.002	1.708 (0)	
	=loadings[c]		1.000	.005	.004	2.029 (2)	
	=intercepts[c]		.999	.030	.009	9.530 (6)	7.501 (4)
Non-White stereotypes (no FIML)	*unconstrained*	650	.972	.089	.043	236.354 (39)	
	=loadings		.972	.082	.045	241.409 (45)	5.066 (6)
	=intercepts		.972	.076	.043	248.986 (53)	7.577 (8)

Note: χ^2 was significant for all models at the p < .001 level. To save space, significance indicators are omitted for the χ^2 column.

[a] Model converged with a warning that the covariance matrix of the residuals of the observed variables was not positive definite.

[b] Non-White FT unconstrained model is underidentified/just identified (df = 0).
[c] Model converged with a warning that the variance-covariance matrix of the estimated parameters might not be positive definite and that the smallest eigenvalue was close to 0.

a.



b.

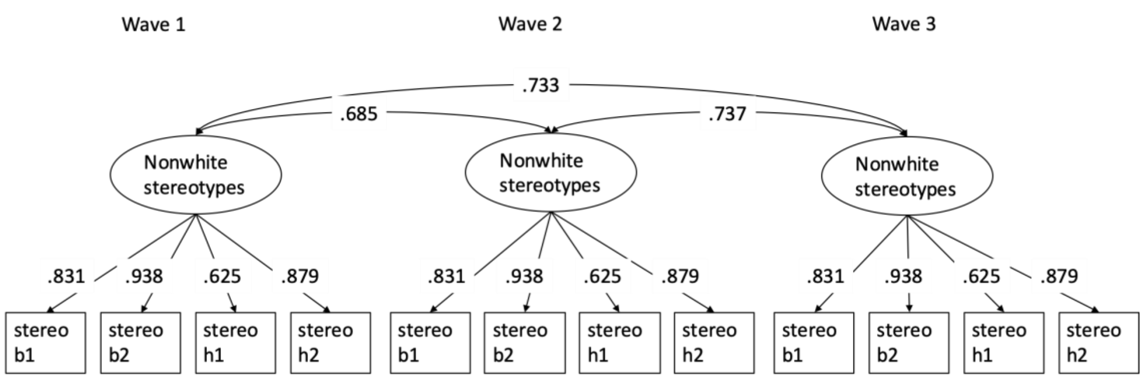


Figure 6. Study 1 final longitudinal CFA models for nonwhite feeling thermometers (a) and nonwhite stereotypes (b), showing standardized coefficients. Both models have equal (unstandardized) factor loadings and intercepts across waves. Item residual autocorrelations are omitted for readability.

Policy attitudes. To make sure the policy items loaded onto 3 separate factors—immigration, criminal justice, and affirmative action—a 3-factor cross-sectional model was examined for each wave. Because the item about the number of people in prison only had 3 response options, I tested both a model treating that variable as continuous and a model treating it as ordered categorical. The continuous indicators model fit well based on CFI (.966-.974) and SRMR (.038-.040) but not RMSEA (.069-.076) in every wave; the model with the categorical indicator fit well based on all non-robust fit statistics (CFI = .993-.999; RMSEA = .016-.036; SRMR = .036-.040) but not robust CFI (.904-.933) or RMSEA (.072-.084). Fit statistics for both the cross-sectional and longitudinal CFA models are presented in Table 12.

Table 12

Study 1 Policy Attitude CFA Fit Statistics

		N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
3-factor, continuous indicators							
Wave 1		985	.968	.072	.040	103.123 (17)	
Wave 2		783	.966	.076	.039	93.738 (17)	
Wave 3		646	.974	.069	.038	69.782 (17)	
Longitudinal (FIML)	*unconstr*[a]	988	.986	.032	.041	381.795 (192)	
	=loadings[a]		.986	.031	.043	392.873 (202)	11.078 (10)
	=intercepts[a]		.985	.030	.044	417.633 (218)	24.760 (16)[+]
3-factor, categorical crim indicator							
Wave 1		985	.993/ .904	.036/ .084	.040	39.019/ 135.613 (17)	

Wave 2		783	.996/ .920	.029/ .079	.039	28.253/ 101.017 (17)	
Wave 3		646	.999/ .933	.016/ .072	.036	19.954/ 74.410 (17)	
Longitudinal (pairwise deletion)	*unconstr*[a]	988	.999/ .932	.015/ .046	.038	232.577/ 588.609 (192)	
	=*loadings*[a]		.998/ .953	.018/ .037	.041	267.556/ 476.758 (202)	34.979 (10)***
	=*intercepts*[a,b]		.998/ .951	.017/ .037	.041	278.418/ 499.033 (215)	10.862 (13)
Immigration							
FIML	*unconstr*	988	.999	.017	.011	19.485 (15)	
	=*loadings*		.999	.018	.022	24.901 (19)	5.416 (4)
	=*intercepts*		.999	.010	.023	27.394 (25)	2.493 (6)
no FIML	*unconstr*	649	.999	.023	.011	20.105 (15)	
	=*loadings*		.998	.022	.023	24.876 (19)	4.771 (4)
	=*intercepts*		.999	.012	.021	27.350 (25)	2.474 (6)
Criminal justice							
continuous indicators, FIML	*unconstr*	988	1.000	.010	.009	16.609 (15)	
	=*loadings*		1.000	.000	.011	17.646 (19)	1.037 (4)
	=*intercepts*		1.000	.000	.013	24.140 (25)	6.494 (6)
categorical indicator, pairwise deletion	*unconstr*	988	1.000/ 1.000	.000/ .000	.010	2.048/ 11.811 (15)	
	=*loadings*		1.000/ 1.000	.000/ .000	.011	2.561/ 10.963 (19)	0.513 (4)

	=*intercepts*[b]		1.000/ 1.000	.000/ .000	.011	4.060/ 13.850 (22)	1.499 (3)
continuous indicators, no FIML	*unconstr*	646	1.000	.010	.010	15.920 (15)	
	=*loadings*		1.000	.000	.014	18.035 (19)	2.115 (4)
	=*intercepts*		.999	.017	.017	29.844 (25)	11.809 (6)$^{+}$
categorical indicator, list-wise deletion	*unconstr*	646	1.000/ 1.000	.000/ .000	.010	2.126/ 13.556 (15)	
	=*loadings*		1.000/ 1.000	.000/ .000	.014	4.125/ 14.936 (19)	1.999 (4)
	=*intercepts*[b]		1.000/ 1.000	.000/ .003	.014	7.431/ 22.128 (22)	3.306 (3)
Affirmative action (FIML)	*unconstr*[c,d]	988	.998	.000	.004	6.191 (0)	
	=*loadings*[d]		.998	.062	.012	9.481 (2)	3.290 (2)
	=*intercepts*[d]		.995	.055	.021	24.176 (6)	14.695 (4)**

[a] Model converged with a warning that the covariance matrix of latent variables was not positive definite.
[b] Model converged with a warning that the variance-covariance matrix of the estimated parameters might not be positive definite and that the smallest eigenvalue was close to 0.
[c] Affirmative action unconstrained model is underidentified/just identified (df = 0).
[d] Negative residual variances (and corresponding impossible loadings) for affirmative action in employment item.

Longitudinal 3-factor CFA models with full-information maximum likelihood estimation or pairwise deletion appeared to fit well (continuous indicators: CFI = .986, RMSEA = .034, SRMR = .041; categorical number of people in prison item: non-robust CFI = .999, robust CFI = .932, non-robust RMSEA = .015, robust RMSEA = .046, SRMR = .038) but resulted in warnings that the covariance matrix of latent variables was not positive definite. Because my hypotheses treat the three policy areas as separate, I then fit 1-factor longitudinal CFA models for each policy area separately for factor score generation. Fit statistics for longitudinal models with both FIML/pairwise deletion and list-wise deletion are presented in Table 11. The unconstrained models for immigration attitudes and criminal justice attitudes fit well, regardless of whether the number of people in prison variable was treated as continuous or categorical and regardless of whether FIML/pairwise deletion or list-wise deletion was used. However, a 1-factor unconstrained model for affirmative action attitudes was just identified, and one of the items had an impossibly high factor loading and a negative residual covariance. Because the two affirmative action items were highly correlated with each other in each wave (W1 *r* = .738, W2 *r* = .742, W3 *r* = .790), composite scores seemed more appropriate for further analyses than factor scores generated from potentially problematic longitudinal CFA models. Internal consistency for immigration attitudes and criminal justice attitudes was lower than expected—α = .73-.74 for immigration and α = .67-.74 for criminal justice—so factor scores seemed more appropriate for those policy areas.

In models with list-wise deletion, constraining loadings to be equal across waves did not significantly affect fit for immigration attitudes ($\chi^2_{19} = 24.876, \chi^2_{15} = 20.105, \Delta\chi^2_4 = 4.771, p = .312$), criminal justice attitudes with continuous indicators ($\chi^2_{19} = 18.035, \chi^2_{15} = 15.920, \Delta\chi^2_4 = 2.115, p = .715$), or criminal justice attitudes with the number of people in prison item treated as ordered categorical ($\chi^2_{19} = 4.125, \chi^2_{15} = 2.126, \Delta\chi^2_4 = 1.999, p = .736$). Constraining intercepts to be equal across waves also did not affect model fit for immigration attitudes ($\chi^2_{25} = 27.350, \Delta\chi^2_6 = 2.474, p = .871$) but marginally significantly worsened fit for criminal justice attitudes with continuous indicators ($\chi^2_{25} = 29.844, \Delta\chi^2_6 = 11.809, p = .066$). For criminal justice attitudes with the categorical indicator, the equal intercepts model produced a warning that the smallest eigenvalue was close to 0, though model fit was not significantly worse than in the unconstrained model ($\chi^2_{25} = 7.431, \Delta\chi^2_6 = 3.306, p = .770$). Based on these results, factor scores for immigration attitudes were generated based on the equal intercepts model, and factor scores for criminal justice attitudes were generated based on the equal loadings models, with separate factor scores from the model with continuous indicators and the model with the number of people in prison variable treated as ordered categorical. (Equal loadings models were used for both versions of the criminal justice attitude factor scores to keep them as comparable as possible.) The standardized version of the final immigration attitude model is presented in Figure 7; the standardized versions of the final criminal justice attitude models are presented in Figure 8.

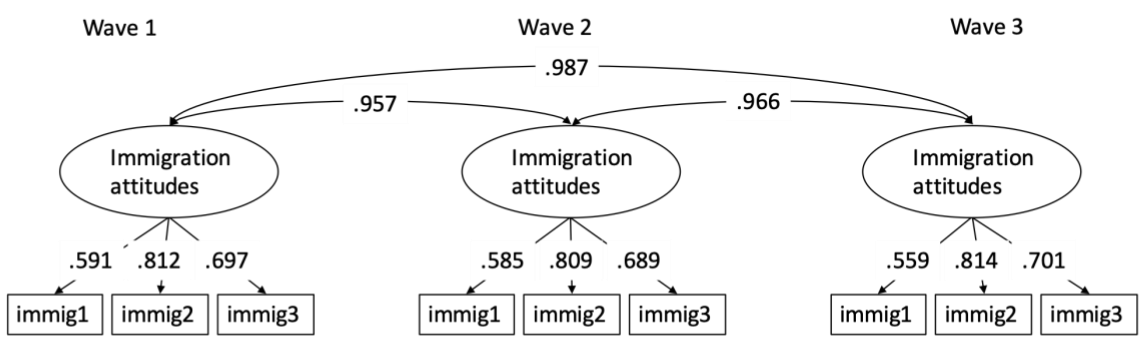
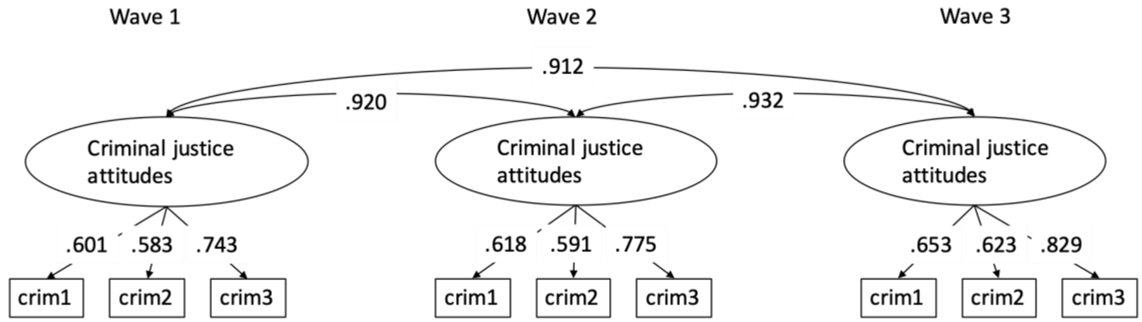


Figure 7. Study 1 final longitudinal CFA model for immigration attitudes, showing standardized coefficients. The model has equal (unstandardized) factor loadings and intercepts across waves. Item residual autocorrelations are omitted for readability.

a.



b.

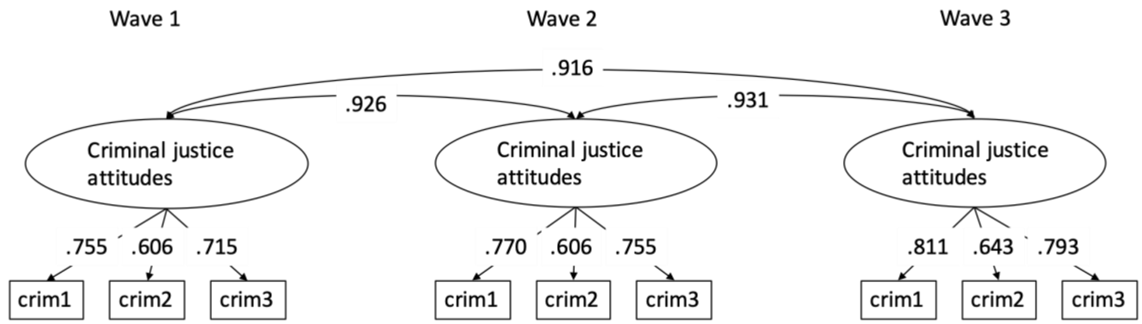


Figure 8. Study 1 final longitudinal CFA models for criminal justice attitudes, with the number of people in prison item treated as continuous (a) and categorical (b), showing standardized coefficients. Both models have equal (unstandardized) loadings across waves. Item residual autocorrelations are omitted for readability.

Potential mediators. One-factor cross-sectional CFA models were examined separately for efficacy and for all of the other items (which the pilot study EFA indicated were part of a single factor, and which I refer to in this analysis as "relative deprivation"). Neither model fit well in any wave (efficacy: CFI = .710-.779, RMSEA = .337-.430, SRMR = .085-.100; relative deprivation: CFI = .729-.776, RMSEA = .186-.200, SRMR = .090-.113). Adding shared method error covariances to the efficacy model (i.e., covariances between similarly worded items across the two identities) led to a warning that the information matrix could not be inverted. Because one of the largest modification indices in the relative deprivation model suggested a covariance between the two linked fate scores, I tested a 2-factor model with the linked fate items on one factor and the remaining items on the other (which fits identically to a 1-factor model with error covariance between the two linked fate items). This model also did not fit well (CFI = .830-.850, RMSEA = .153-.161, SRMR = .075-.091), but adding error covariances among the perceived discrimination items resulted in at least meeting the criterion for SRMR (.061-.072).

I also examined models with all of the potential mediator items. A 2-factor model with efficacy and relative deprivation as the factors fit poorly (CFI = .698-.754, RMSEA = .143-.160, SRMR = .089-.111). A 3-factor model separating linked fate from relative deprivation also did not meet fit criteria (CFI = .778-.814, RMSEA = .126-.139, SRMR = .081-.096). Adding error covariances among the perceived discrimination items met the SRMR criterion in Wave 1 (SRMR = .075). Adding shared method error covariances for the efficacy items resulted in negative residual variances. Fit statistics for the cross-sectional CFA models are presented in Table 13.

Table 13

Study 1 Potential Mediators Cross-sectional CFA Fit Statistics

	Wave 1				**Wave 2**				**Wave 3**			
	N	*CFI*	*RMSEA*	*SRMR*	*N*	*CFI*	*RMSEA*	*SRMR*	*N*	*CFI*	*RMSEA*	*SRMR*
Efficacy	987				784				649			
no error covariances		.748	.359	.086		.779	.337	.085		.710	.430	.100
shared method cov[a]		.834	0	.108		.854	0	.074		.844	0	.139
Relative deprivation 1-factor	807	.776	.186	.090	629	.772	.186	.093	530	.729	.200	.113
Relative deprivation 2-factor	807				629				530			
no error cov		.843	.158	.075		.850	.153	.076		.830	.161	.091
PD cov		.912	.126	.061		.912	.125	.063		.923	.115	.072
2-factor model (RD + Eff)	806	.754	.143	.089	629	.748	.144	.100	529	.698	.160	.111
3-factor model (LF + RD + Eff)	806				629				529			
no error cov		.809	.128	.081		.814	.126	.090		.778	.139	.096
PD cov		.863	.111	.075		.862	.111	.084		.847	.119	.088
eff shared method cov		.836	.120[b]	.070		.839	.119[b]	.067		.820	.127[b]	.084
PD cov & eff shared method cov		.889	.101[b]	.063		.887	.103[+]	.061		.888	.103[b]	.075

[a] Information matrix could not be inverted. Standard errors not available.
[b] Negative residual variances for some observed variables.
[c] Model converged with a warning that the covariance matrix of observed variables was not positive definite

Longitudinal CFA models were initially tested using FIML. A 1-factor model for efficacy met the fit criterion for SRMR (.069) but not for CFI (.847) or RMSEA (.127). A 1-factor model for relative deprivation did not meet the criteria for any of the fit statistics (CFI = .854, RMSEA = .082, SRMR = .092). A 2-factor relative deprivation model with within-wave error covariances among the perceived discrimination items fit well based on RMSEA (.060) and SRMR (.079) but not CFI (.926). I also fit a 3-factor relative deprivation model that separated the perceived discrimination items from the remaining "relative deprivation" items; this model nearly met fit criteria (CFI = .945, RMSEA = .053, SRMR = .055) without any within-wave error covariances. Combining the 3-factor relative deprivation model with a factor for the efficacy items produced a 4-factor model that fit based on RMSEA (.051) and SRMR (.072) but not CFI (.912). Adding within-wave shared method covariances for the efficacy items appeared to improve fit, although CFI was still less than ideal (CFI = .922, RMSEA = .048, SRMR = .069).

I re-fit the relative deprivation 3-factor model and the mediator 4-factor model using list-wise deletion for missing data. The relative deprivation model fit based on SRMR (.060) and was close to but did not quite meet the criteria for CFI or RMSEA (CFI = .945, RMSEA = .062). However, the 4-factor mediator model did not fit well (CFI = .898, RMSEA = .064, SRMR = .085). Adding within-wave shared method covariances for the efficacy items brought RMSEA down to .060 (good fit) and SRMR down to .082 (almost a good fit), but CFI (.911) was still low. I also tested models (using both FIML and list-wise deletion) with both within-wave and between-wave efficacy item shared method covariances, but these models had impossible loadings and negative residual covariances. Fit statistics for mediator item longitudinal CFA models are presented in Table 14.

Table 14

Study 1 Potential Mediators Longitudinal CFA Fit Statistics

		N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
Efficacy (FIML)		988					
no w/in wave error cov			.847	.127	.069	656.352 (39)	
w/in wave shared method cov			.889	.117	.067	482.835 (33)	
RD 1-factor (FIML)		988	.854	.082	.092	2233.303 (294)	
RD 2-factor (FIML)		988					
no w/in wave error cov			.896	.070	.076	1662.331 (282)	
w/in wave PD cov	*unconst*		.926	.060	.079	1258.879 (273)	
	=loadings		.924	.059	.079	1288.026 (287)	29.147 (14)**
RD 3-factor							
FIML	*unconst*	988	.945	.053	.055	983.846 (261)	
	=loadings		.944	.052	.058	1009.249 (273)	25.403 (12)*
no FIML	*unconst*	421	.945	.062	.060	677.910 (261)	
	=loadings		.943	.061	.064	707.027 (273)	29.117 (12)**
Mediator 2F (eff + RD) (FIML)		988	.840	.066	.091	3450.468 (648)	
Mediator 3F (eff, LF, RD) (FIML)		988	.874	.060	.081	2832.968 (627)	
Mediator 4F (eff, LF, PD, RD)							
	unconst	988	.912	.051	.072	2138.736 (597)	

no w/in wave error cov, FIML	*=loadings*		.911	.051	.073	2172.509 (615)	33.773 (18)*
w/in wave eff cov, FIML	*unconst*	988	.922	.048	.069	1962.581 (591)	
	=loadings		.921	.048	.070	1993.737 (609)	31.156 (18)*
w/in & between-wave eff cov, FIML[a]		988	.929	.047	.060	1824.094 (579)	
no w/in wave error cov, no FIML	*unconst*	420	.898	.064	.085	1623.945 (597)	
	=loadings		.897	.064	.086	1659.367 (615)	35.422 (18)**
w/in wave eff cov, no FIML	*unconst*	420	.911	.060	.082	1485.956 (591)	
	=loadings		.910	.060	.084	1520.993 (609)	35.037 (18)**
w/in & between-wave eff cov, no FIML[a]		420	.921	.057	.075	1372.118 (579)	

[a] Negative residual variances (and corresponding impossible loadings) for Asian American efficacy item 1.

For the 4-factor model with within-wave error covariances for the efficacy items, constraining loadings to be equal across waves resulted in significantly worse fit ($\chi^2_{609} = 1993.737, \chi^2_{591} = 1962.581, \Delta\chi^2_{18} = 31.156, p = .028$). Because it appeared to provide the best fit for the full set of mediator items and because equality constraints significantly reduced fit, I used the unconstrained 4-factor model with efficacy shared method error covariances to generate factor scores for efficacy, linked fate, perceived discrimination, and relative deprivation. The standardized version of the final longitudinal CFA model for the mediator items is presented in Figure 9.

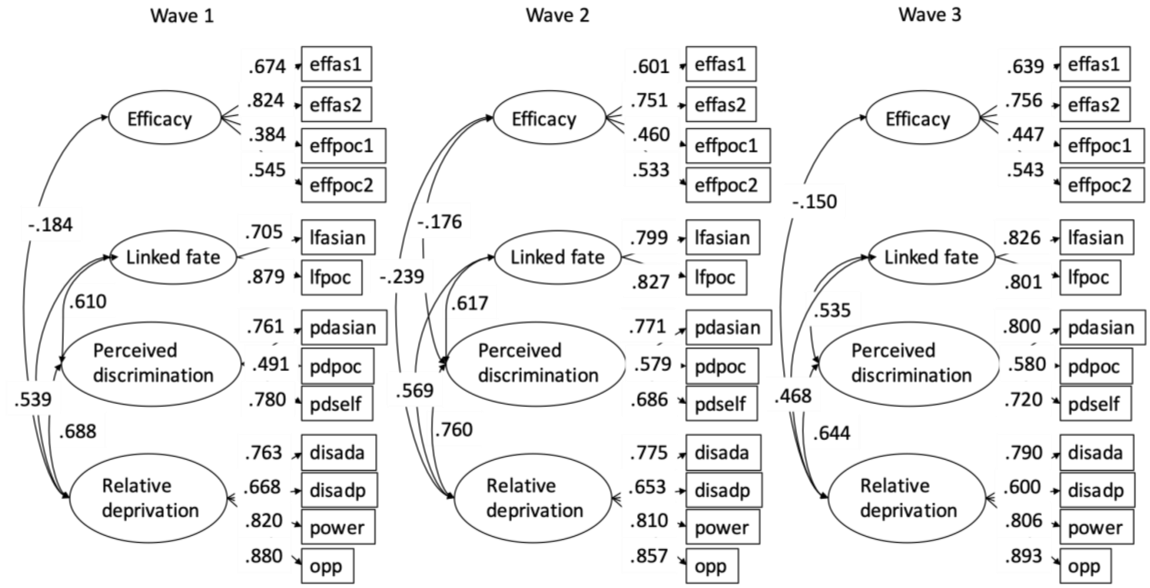


Figure 9. Study 1 final 4-factor longitudinal CFA model for mediator items, showing standardized coefficients and significant within-wave factor correlations. The four factors were efficacy, linked fate, perceived discrimination, and relative deprivation, and the model included within-wave shared method covariances for the Asian American and POC versions of each efficacy item. Item residual covariances, cross-wave factor covariances, and non-significant within-wave factor covariances are omitted for readability.

3. Identity and Racial Attitudes

I hypothesized based on the common ingroup identity model that 1) identification as POC would predict more positive attitudes toward Black and Latino Americans (Hypothesis 2); 2) identification as American would predict more positive attitudes toward Black and Latino Americans (Hypothesis 1); and 3) identification as American would predict more positive attitudes toward Whites (Hypothesis 1).

Cross-lagged panel models and random-intercepts cross-lagged panel models were used to test these hypotheses. CLPM was used to test whether between-person differences in identity importance at Time 1 predict changes in racial attitudes (relative to other people) from Time 1 to Time 2 (cf. Orth et al., 2020). However, the CLPM lagged and cross-lagged coefficients conflate between-person and within-person effects (Hamaker et al., 2015). By separating stable between-person variance from within-person variance over time, RI-CLPM could provide two pieces of information: 1) whether, at the between-person level, stable individual differences in identity and racial attitudes are correlated with each other and 2) whether within-person variation in identity predicts within-person changes in racial attitudes.

CLPM and RI-CLPM were analyzed through structural equation modeling using the lavaan package in R. For each identity-attitude pair, I tested CLPM with and without demographic and political covariates[4] and with and without stationarity across lags, and I tested RI-CLPM with and without stationarity.

a. Cross-lagged panel models (CLPM). Fit statistics for the identity-racial attitude panel models are provided in Tables 15-18. CLPM models with nonwhite FTs appeared to fit well based on CFI and SRMR (CFI ≥ .95, SRMR ≤ .08), but RMSEA was high across identities and models (.146-.218 for Asian American identity, .137-.206 for POC identity, .176-.252 for American identity). Models with nonwhite stereotypes met the criteria for SRMR but not always for CFI (.910-.944 for Asian American identity,

[4] Because two of the demographic covariates, foreign-born and age of arrival in the U.S., are in a sense perfectly collinear (only foreign-born respondents have a value for age of arrival), I fit separate models with all of the other covariates plus foreign-born and all of the other covariates plus age of arrival.

.928-.956 for POC identity, .917-.945 for American identity) and not for RMSEA (.225-.322 for Asian American identity, .210-.313 for POC identity, .245-.360 for American identity). White FTs and stereotypes showed similar patterns (FT: CFI = .929-.963, RMSEA = .190-.302; stereotypes: CFI = .936-.975, RMSEA = .153-.266). Less than ideal model fit as measured by CFI and RMSEA is not unexpected for CLPM with real data, however (see Orth et al., 2021).

Stationarity constraints significantly worsened model fit for some identity-attitude pairs but not others, but no clear pattern emerged for when this was the case (see right column of Tables 15-18). Parameter estimates reported in this section are from the models without covariates, unless otherwise specified, and I indicate whether they come from models with or without stationarity.

Table 15

Study 1 Panel Model Fit Statistics: Nonwhite FTs

	N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Asian American ID						
CLPM Model 1	631	.962	.218	.028	123.907 (4)***	
CLPM Model 1 w/ stationarity	631	.961	.156	.033	130.726 (8)***	6.819 (4)
CLPM Model 2	613	.973	.218	.010	120.394 (4)***	
CLPM Model 2 w/ stationarity	613	.972	.156	.012	127.989 (8)***	7.595 (4)
CLPM Model 3	126	.979	.204	.010	24.928 (4)***	
CLPM Model 3 w/ stationarity	126	.978	.146	.014	29.519 (8)***	4.591 (4)
RI-CLPM	631	1.000	.000	.000	0.001 (1)	123.906 (3)***
RI-CLPM w/ stationarity	631	.998	.046	.026	11.546 (5)*	11.545 (4)*
IV: POC ID						
CLPM Model 1	631	.971	.203	.023	108.279 (4)***	
CLPM Model 1 w/ stationarity	631	.971	.145	.027	113.591 (8)***	5.312 (4)
CLPM Model 2	613	.978	.206	.008	108.152 (4)***	
CLPM Model 2 w/ stationarity	613	.978	.145	.009	110.501 (8)***	2.349 (4)
CLPM Model 3	129	.986	.168	.007	18.200 (4)**	
CLPM Model 3 w/ stationarity	126	.982	.137	.014	26.942 (8)**	8.742 (4)†
RI-CLPM	631	1.000	.000	.002	0.144 (1)	108.135 (3)***
RI-CLPM w/ stationarity	631	1.000	.017	.014	5.951 (5)	5.807 (4)
IV: American ID						
CLPM Model 1	631	.960	.252	.023	164.457 (4)***	
CLPM Model 1 w/ stationarity	631	.958	.182	.027	175.385 (8)***	10.928 (4)*
CLPM Model 2	613	.971	.245	.008	151.677 (4)***	
CLPM Model 2 w/ stationarity	613	.970	.176	.009	159.628 (8)***	7.951 (4)†
CLPM Model 3	126	.977	.237	.007	32.197 (4)***	
CLPM Model 3 w/ stationarity	126	.973	.179	.012	40.237 (8)***	8.040 (4)†

RI-CLPM	631	1.000	.000	.004	0.354 (1)	164.103 (3)***
RI-CLPM w/ stationarity	631	1.000	.000	.012	4.203 (5)	3.849 (4)

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 16

Study 1 Panel Model Fit Statistics: Nonwhite Stereotypes

	N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Asian American ID						
CLPM Model 1	625	.912	.318	.053	256.202 (4)***	
CLPM Model 1 w/ stationarity	625	.910	.227	.057	266.088 (8)***	9.886 (4)*
CLPM Model 2	607	.936	.322	.019	255.510 (4)***	
CLPM Model 2 w/ stationarity	607	.935	.231	.021	267.067 (8)***	11.557 (4)*
CLPM Model 3	125	.944	.320	.018	55.175 (4)***	
CLPM Model 3 w/ stationarity	125	.944	.225	.020	58.772 (8)***	3.597 (4)
RI-CLPM	625	1.000	.000	.004	0.390 (1)	255.812 (3)***
RI-CLPM w/ stationarity	625	.995	.065	.036	18.267 (5)**	17.877 (4)**
IV: POC ID						
CLPM Model 1	625	.929	.306	.050	238.315 (4)***	
CLPM Model 1 w/ stationarity	625	.928	.219	.052	247.206 (8)***	8.891 (4)†
CLPM Model 2	607	.946	.313	.018	242.435 (4)***	
CLPM Model 2 w/ stationarity	607	.945	.224	.019	250.852 (8)***	8.417 (4)†
CLPM Model 3	125	.956	.293	.016	46.981 (4)***	
CLPM Model 3 w/ stationarity	125	.955	.210	.019	51.997 (8)***	5.016 (4)
RI-CLPM	625	1.000	.000	.005	0.719 (1)	237.596 (3)***

RI-CLPM w/ stationarity	625	.999	.033	.020	8.393 (5)	7.674 (4)
IV: American ID						
CLPM Model 1	625	.921	.341	.050	295.514 (4)***	
CLPM Model 1 w/ stationarity	625	.917	.248	.056	314.579 (8)***	19.065 (4)***
CLPM Model 2	607	.941	.341	.018	286.584 (4)***	
CLPM Model 2 w/ stationarity	607	.939	.245	.020	300.154 (8)***	13.570 (4)**
CLPM Model 3	125	.943	.360	.016	68.769 (4)***	
CLPM Model 3 w/ stationarity	125	.945	.250	.018	70.706 (8)***	1.937 (4)
RI-CLPM	625	1.000	.000	.001	0.017 (1)	295.497 (3)***
RI-CLPM w/ stationarity	625	.997	.063	.032	17.445 (5)**	17.428 (4)**

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 17

Study 1 Panel Model Fit Statistics: White FT

	N	**CFI**	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
IV: Asian American ID						
CLPM Model 1	627	.937	.272	.041	189.526 (4)***	
CLPM Model 1 w/ stationarity	627	.929	.204	.050	216.167 (8)***	26.641 (4)***
CLPM Model 2	609	.956	.269	.015	180.542 (4)***	
CLPM Model 2 w/ stationarity	609	.952	.199	.017	201.413 (8)***	20.871 (4)***
CLPM Model 3	124	.954	.284	.015	44.132 (4)***	
CLPM Model 3 w/ stationarity	124	.949	.213	.020	52.805 (8)***	8.673 (4)†
RI-CLPM	627	1.000	.000	.001	0.033 (1)	189.493 (3)***
RI-CLPM w/ stationarity	627	.993	.079	.036	24.351 (5)***	24.318 (4)***

IV: POC ID						
CLPM Model 1	627	.945	.269	.039	185.327 (4)***	
CLPM Model 1 w/ stationarity	627	.945	.190	.040	188.901 (8)***	3.574 (4)
CLPM Model 2	609	.960	.271	.014	182.388 (4)***	
CLPM Model 2 w/ stationarity	609	.960	.191	.015	186.150 (8)***	3.762 (4)
CLPM Model 3	124	.963	.262	.013	38.033 (4)***	
CLPM Model 3 w/ stationarity	124	.956	.203	.017	48.995 (8)***	10.962 (4)*
RI-CLPM	627	.999	.066	.013	3.728 (1)†	181.599 (3)***
RI-CLPM w/ stationarity	627	1.000	.023	.016	6.651 (5)	2.923 (4)
IV: American ID						
CLPM Model 1	627	.944	.293	.038	218.639 (4)***	
CLPM Model 1 w/ stationarity	627	.944	.208	.040	225.689 (8)***	7.050 (4)
CLPM Model 2	609	.960	.285	.013	201.496 (4)***	
CLPM Model 2 w/ stationarity	609	.959	.203	.015	208.112 (8)***	6.616 (4)
CLPM Model 3	124	.960	.302	.013	49.169 (4)***	
CLPM Model 3 w/ stationarity	124	.959	.216	.017	54.238 (8)***	5.069 (4)
RI-CLPM	627	1.000	.000	.002	0.110 (1)	218.529 (3)***
RI-CLPM w/ stationarity	627	1.000	.007	.016	5.156 (5)	5.046 (4)

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 18

Study 1 Panel Model Fit Statistics: White Stereotypes

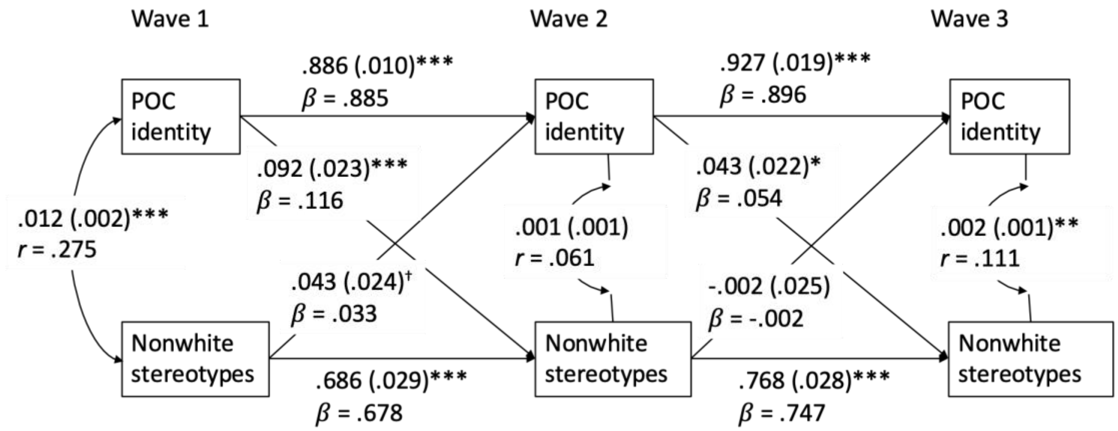
	N	**CFI**	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
IV: Asian American ID						

CLPM Model 1	632	.939	.242	.048	152.156 (4)***	
CLPM Model 1 w/ stationarity	632	.936	.175	.051	162.833 (8)***	10.677 (4)*
CLPM Model 2	614	.959	.240	.017	145.023 (4)***	
CLPM Model 2 w/ stationarity	614	.958	.172	.018	154.047 (8)***	9.024 (4)†
CLPM Model 3	126	.967	.232	.014	31.128 (4)***	
CLPM Model 3 w/ stationarity	126	.967	.163	.018	34.773 (8)***	3.645 (4)
RI-CLPM	632	1.000	.000	.004	0.257 (1)	151.899 (3)***
RI-CLPM w/ stationarity	632	.996	.054	.033	14.349 (5)*	14.092 (4)**
IV: POC ID						
CLPM Model 1	632	.950	.235	.045	143.992 (4)***	
CLPM Model 1 w/ stationarity	632	.950	.166	.046	147.894 (8)***	3.902 (4)
CLPM Model 2	614	.965	.235	.016	139.859 (4)***	
CLPM Model 2 w/ stationarity	614	.965	.165	.017	142.252 (8)***	2.393 (4)
CLPM Model 3	126	.975	.208	.013	25.899 (4)***	
CLPM Model 3 w/ stationarity	126	.973	.153	.017	31.580 (8)***	5.681 (4)
RI-CLPM	632	.999	.054	.014	2.874 (1)†	141.118 (3)***
RI-CLPM w/ stationarity	632	.997	.049	.028	12.616 (5)*	9.742 (4)*
IV: American ID						
CLPM Model 1	632	.946	.266	.043	182.566 (4)***	
CLPM Model 1 w/ stationarity	632	.945	.189	.045	188.964 (8)***	6.398 (4)
CLPM Model 2	614	.962	.258	.016	166.947 (4)***	
CLPM Model 2 w/ stationarity	614	.963	.181	.016	169.690 (8)***	2.743 (4)
CLPM Model 3	126	.974	.234	.010	31.697 (4)***	
CLPM Model 3 w/ stationarity	126	.971	.174	.017	38.522 (8)***	6.825 (4)
RI-CLPM	632	1.000	.026	.011	1.427 (1)	181.139 (3)***
RI-CLPM w/ stationarity	632	1.000	.012	.020	5.476 (5)	5.049 (4)

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Consistent with Hypothesis 2, higher POC identification (as measured by the Huddy et al. scale items) predicted higher ratings on nonwhite stereotypes (model without covariates: Wave 1-2: $b = .092$, $SE = .023$, $p < .001$, $\beta = .116$; Wave 2-3: $b = .043$, $SE = .022$, $p = .048$, $\beta = .054$), as shown in Figure 10a. (Lagged and cross-lagged coefficients for all models are presented in Appendix C.) Higher POC identification also predicted higher nonwhite FT ratings (with stationarity: $b = .031$, $SE = .014$, $p = .023$, $\beta = .038$ & $.039$), at least between Waves 1 and 2 ($b = .057$, $SE = .020$, $p = .005$, $\beta = .069$) (see Figure 10b for model with stationarity). Thus, respondents who identified more as POC tended to show improvements in nonwhite stereotype ratings and possibly nonwhite FT ratings, at least from Wave 1 to Wave 2, compared to respondents who identified less as POC.

a.



b.

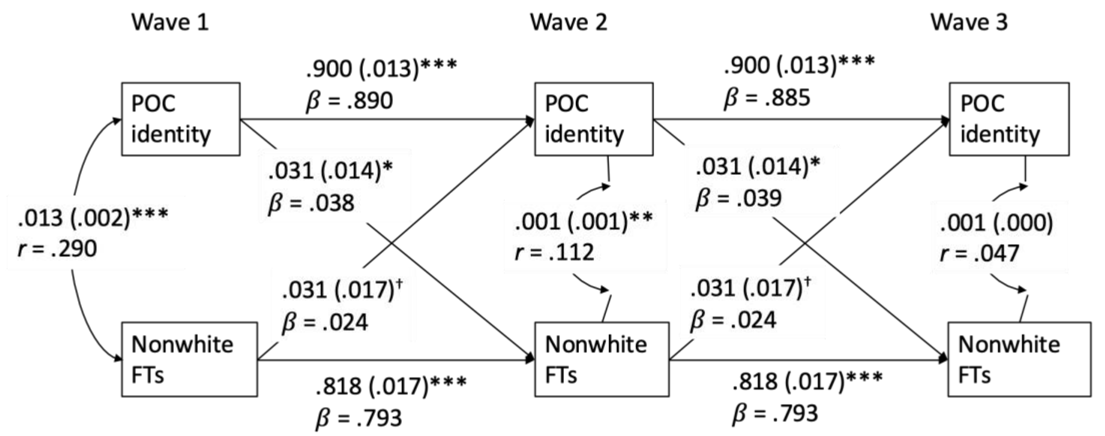
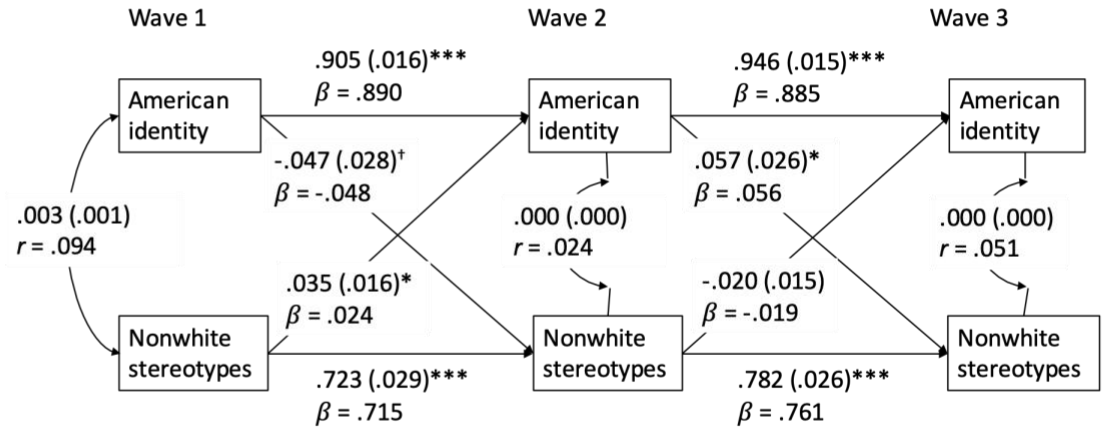


Figure 10. Study 1 CLPM for POC identity and nonwhite stereotypes, without covariates and with no stationarity constraints (a), and POC identity and nonwhite feeling thermometers (FT), without covariates and with stationarity constraints on lagged and cross-lagged effects (b). Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

However, the identity-FT cross-lagged coefficients are not significant for the Wave 2-3 time lag unless stationarity across time lags is assumed, and the same is true for the identity-stereotypes cross-lagged coefficients in models with covariates. The stationarity assumption appears appropriate for POC identity and nonwhite FTs. However, because fit is marginally significantly worse with stationarity for the POC identity-nonwhite stereotypes models with larger sample sizes (i.e., the models without covariates and the models with foreign-born as a covariate) (see right column of Table 16) the Wave 2 to Wave 3 cross-lagged effects are less well-supported than the Wave 1 to Wave 2 cross-lagged effects.

Cross-lagged coefficients for American identity and attitudes toward nonwhites are not consistent in either significance or sign across time lags. The cross-lagged effect of American identity on nonwhite stereotypes is negative and marginally significant from Wave 1 to Wave 2 (b = -.047, SE = .028, p = .087, β = -.048) and positive and significant from Wave 2 to Wave 3 (b = .057, SE = .026, p = .029, β = .056); the reverse effect, from stereotypes to identity, switches signs in the opposite direction, though only the positive Wave 1-2 effect is significant (b = .035, SE = .016, p = .035, β = .034). A similar pattern emerges for nonwhite FTs, but only the reverse effects approach significance (W1-W2 b = .034, SE = .016, p = .029, β = .034; W2-W3 b = -.024, SE = .015, p = .097, β = -.025). The results of the CLPM models for American identity and nonwhite stereotypes (a) and FTs (b), without stationarity, are presented in Figure 11. Unsurprisingly in light of the different signs across time lags, the stationarity assumption generally does not hold (see bottom section, right column of Tables 17 & 18). Overall, the CLPM do not provide evidence that Asian Americans who identify more strongly as American feel more positively toward other racial minorities over time.

a.



b.

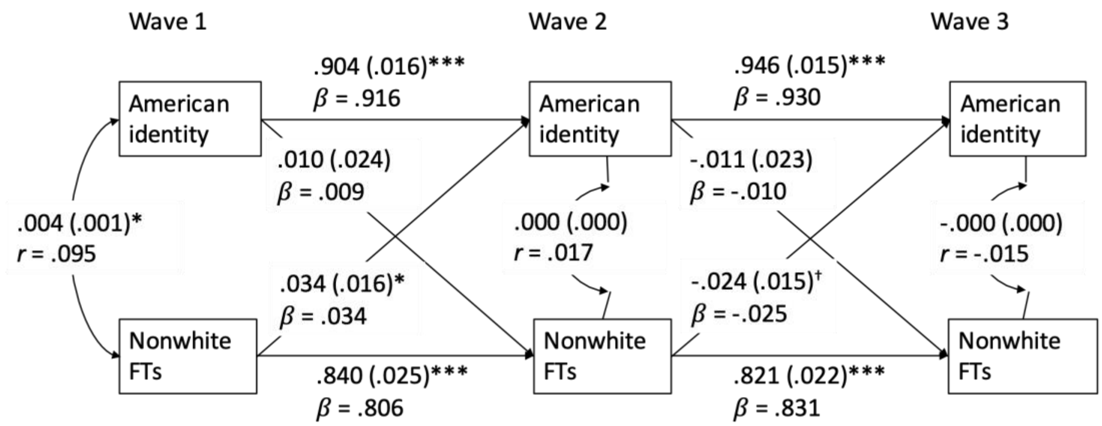


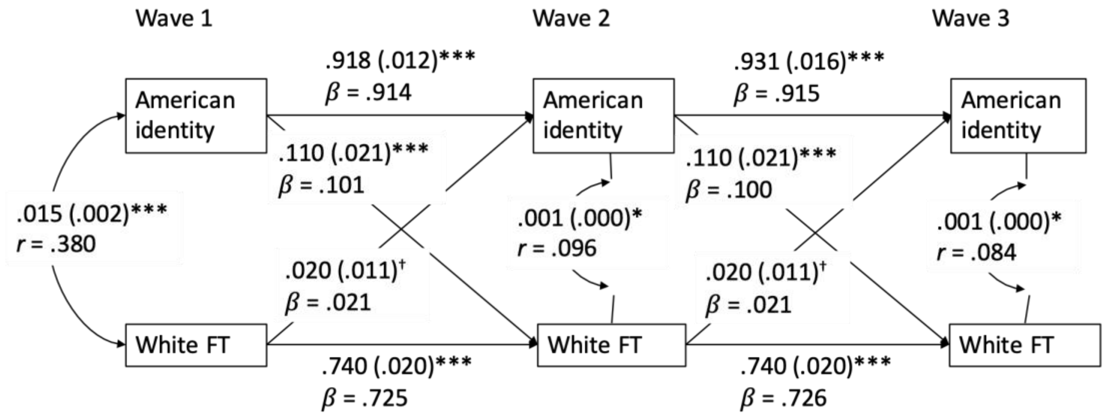
Figure 11. Study 1 CLPM for American identity and nonwhite stereotypes (a) and American identity and nonwhite FTs (b), without covariates and with no stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

However, American identity does show significant, positive cross-lagged effects on both the White FT (with stationarity: $b = .110$, $SE = .021$, $p < .001$, $\beta = .101$ & .100) (Figure 12a) and White stereotypes (with stationarity: $b = .102$, $SE = .021$, $p < .001$, $\beta =$

.108 & .111) (Figure 12b) across most models (see Appendix C for coefficients from additional models).[5] The reverse effect from White FT ratings to American identity is also marginally significant to significant, at least between Wave 2 and Wave 3 (with stationarity: b = .020, SE = .011, p = .070, β = .021; without stationarity: W2-W3 b = .031, SE = .015, p = .035, β = .034). Thus, Asian Americans who identify more as American tend to show improvements in their attitudes toward Whites compared to Asian Americans who identify less as American, but there is also some evidence that Asian Americans with more positive attitudes toward Whites might increase their identification as American compared to those with less positive attitudes toward Whites.

[5] Additionally, in contrast to the nonwhite attitude models, the stationarity assumption holds for all of the American identity – attitudes toward Whites CLPM models (see bottom section, right column of Tables 17 & 18).

a.



b.

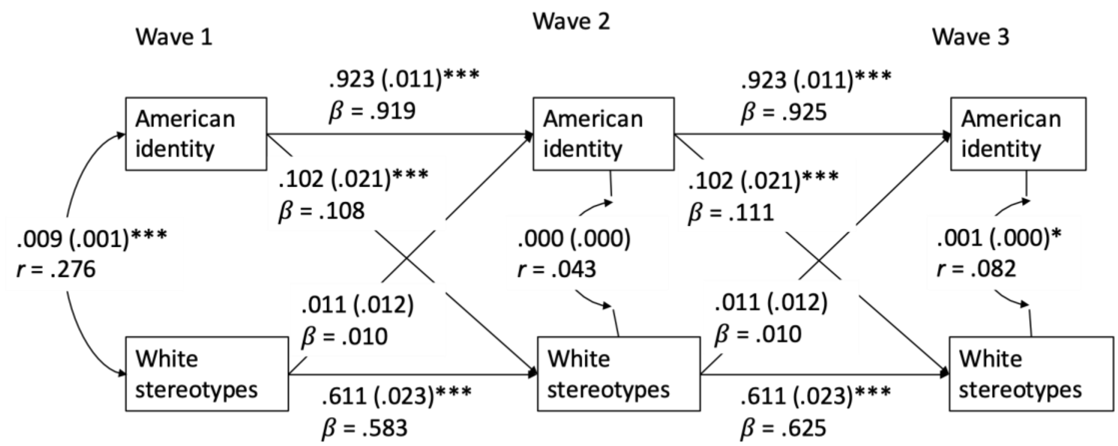


Figure 12. Study 1 CLPM for American identity and the White FT (a) and American identity and White stereotypes (b), without covariates and with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Unexpectedly, Asian American identity also had a significant, positive cross-lagged effect on non-White stereotypes from Wave 2 to Wave 3 ($b = .058$, $SE = .027$, $p = .035$, $\beta = .055$) (Figure 13), and POC identity and the White FT showed negative cross-lagged effects on each other (ID to FT: *b* = -.039, *SE* = .016, *p* = .016, β = -.044; FT to ID: *b* = -.033, *SE* = .015, *p* = .027, β = -.028)[6] (Figure 14). Thus, individual differences in Asian Americans' social identities potentially predict attitudes toward groups that are not included in those identities.

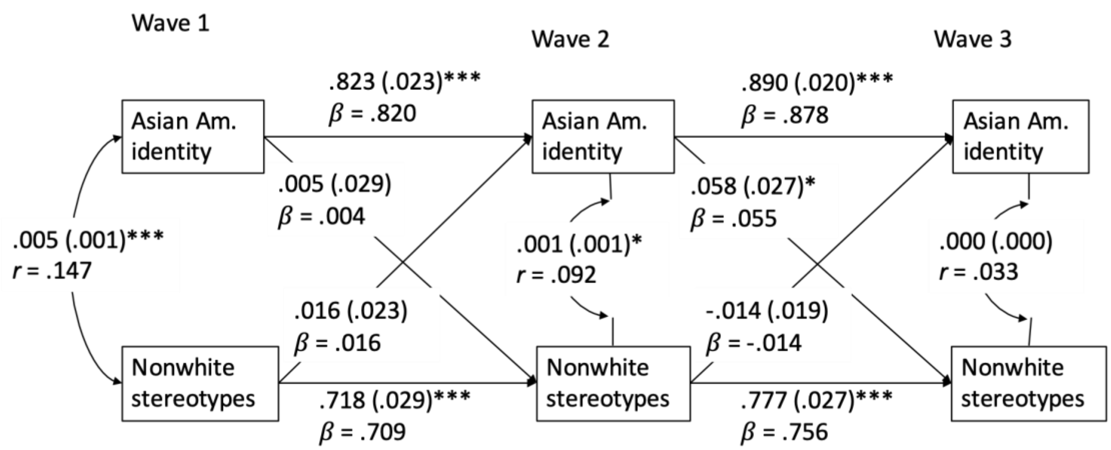


Figure 13. Study 1 CLPM for Asian American identity and nonwhite stereotypes, without covariates and with no stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** *p* < .001, ** *p* < .01, * *p* < .05, † *p* < .10 (marginally significant).

[6] With stationarity, which did not significantly change model fit. Without stationarity, only the Wave 2 to Wave 3 cross-lagged coefficients approached significance.

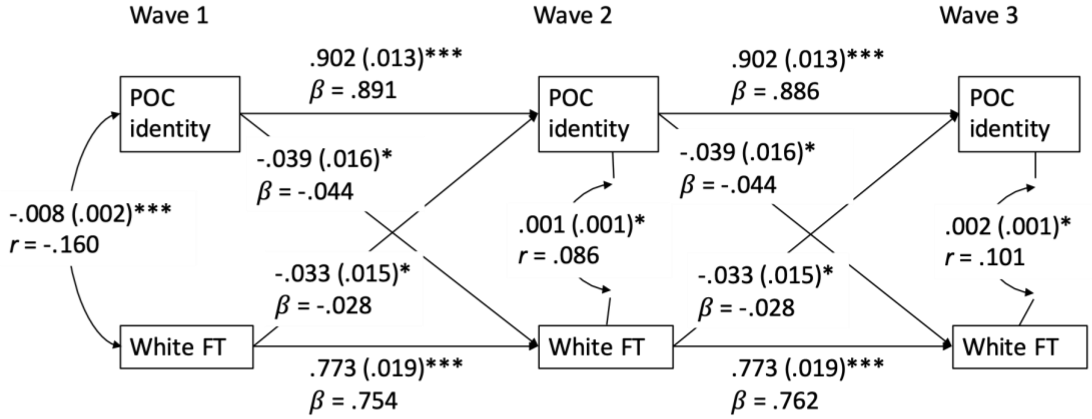


Figure 14. Study 1 CLPM for POC identity and the White FT, without covariates and with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

b. Random-intercepts cross-lagged panel models (RI-CLPM). As one might expect for constructs with trait-like stability (Hamaker et al., 2015; Orth et al., 2021), RI-CLPM produced better model fit than CLPM across identities and racial attitude measures. All identity-racial attitude models met the Hu and Bentler (1999) criteria except Asian American identity and nonwhite stereotypes with stationarity (RMSEA = .065), Asian American identity and White FT with stationarity (RMSEA = .08), and POC identity and White FT without stationarity (RMSEA = .07). However, stationarity constraints significantly worsened model fit for Asian American identity and all racial attitude measures (nonwhite FTs: $\chi^2_5 = 11.546, \chi^2_1 = 0.001, \Delta\chi^2_4 = 11.545, p = .021$; nonwhite stereotypes: $\chi^2_5 = 18.267, \chi^2_1 = 0.390, \Delta\chi^2_4 = 17.877, p = .001$; White FT:

$\chi^2_5 = 24.351, \chi^2_1 = 0.033, \Delta\chi^2_4 = 24.318, p < .001$; White stereotypes: $\chi^2_5 = 14.349, \chi^2_1 = 0.257, \Delta\chi^2_4 = 14.092, p = .007$), American identity and nonwhite stereotypes ($\chi^2_5 = 17.445, \chi^2_1 = 0.017, \Delta\chi^2_4 = 17.428, p = .002$), and POC identity and White stereotypes ($\chi^2_5 = 12.616, \chi^2_1 = 2.874, \Delta\chi^2_4 = 9.742, p = .045$). Fit statistics are presented in Tables 15-18.

Trait-level covariances were significant and in the expected direction for almost every identity-racial attitude pair. POC identity was significantly positively related to nonwhite FT (*c* = .013, *SE* = .002, *p* < .001, *r* = .344) and stereotype ratings (*c* = .012, *SE* = .002, *p* < .001, *r* = .309)[7]. American identity was significantly positively related to White FT (*c* = .016, *SE* = .002, *p* < .001, *r* = .457) and stereotype ratings (*c* = .010, *SE* = .001, *p* < .001, *r* = .404) and to nonwhite stereotype ratings in the model without stationarity (*c* = .003, *SE* = .001, *p* = .046, *r* = .087). However, trait-level covariance between American identity and nonwhite FTs was not significant (*c* = .002, *SE* = .001, *p* = .126, *r* = .073). At the between-person level, then, identification as POC is associated with more positive attitudes toward other minority groups included in the POC common ingroup. Identification as American is associated with more positive attitudes toward Whites, who are part of this common ingroup, but is less clearly associated with attitudes toward other minority groups, who at least in theory are also part of this common ingroup.

[7] Because stationarity did not significantly change model fit for most of the RI-CLPM relevant to my hypotheses about racial attitudes, I report the trait-level covariances from the models with stationarity unless otherwise specified.

As with cross-lagged effects in the CLPM, Asian American identity showed an unexpected positive relationship with nonwhite stereotype ratings (c = .004, SE = .001, p = .001, r = .157)[8]. Additionally, the trait covariance with nonwhite FT ratings was positive and significant (c = .004, SE = .001, p = .006, r = .151). Again, in keeping with the cross-lagged effects in the CLPM, POC identity had a significant, negative trait-level covariance with White FT ratings (c = -.009, SE = .002, p < .001, r = -.215). POC identity also had a marginally significant (and significant with stationarity constraints, though stationarity is not met) negative trait-level covariance with White stereotype ratings (c = -.003, SE = .002, p = .056, r = -.099), and Asian American identity had a marginally significant (also significant with stationarity constraints, but stationarity is not met) positive trait-level covariance with White stereotype ratings (c = .002, SE = .001, p = .068, r = .098).

At the within-person level, the RI-CLPM results are more difficult to interpret. Consistent with the cross-lagged effects in the CLPM, within-person increases in POC identification appeared to predict increased positivity in stereotype ratings of other minority groups (b = .280, SE = .087, p = .001, β = .293 & .265). But the reverse effect is also significant (b = .134, SE = .058, p = .022, β = .141 & .116), and both cross-lagged effects are only significant when stationarity is assumed. (The model with stationarity is shown in Figure 15.) As with the CLPM, POC identification did not have significant cross-lagged effects on nonwhite FT ratings in the RI-CLPM.

[8] Trait-level covariances reported for Asian American identity and racial attitudes are from the models without stationarity because stationarity significantly worsened model fit.

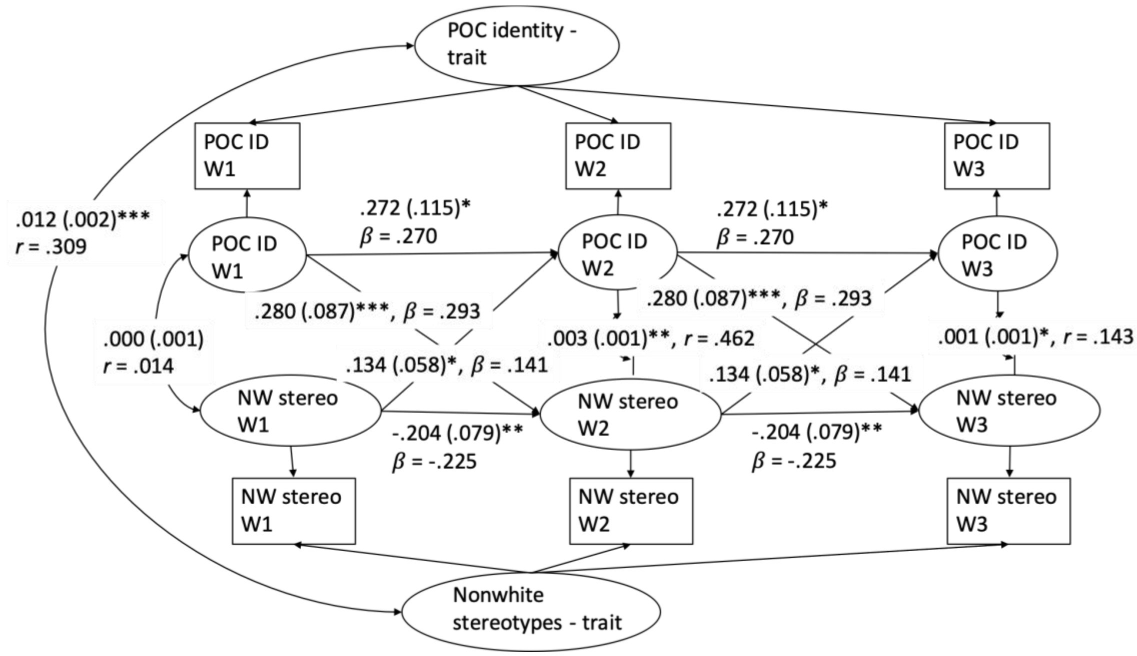
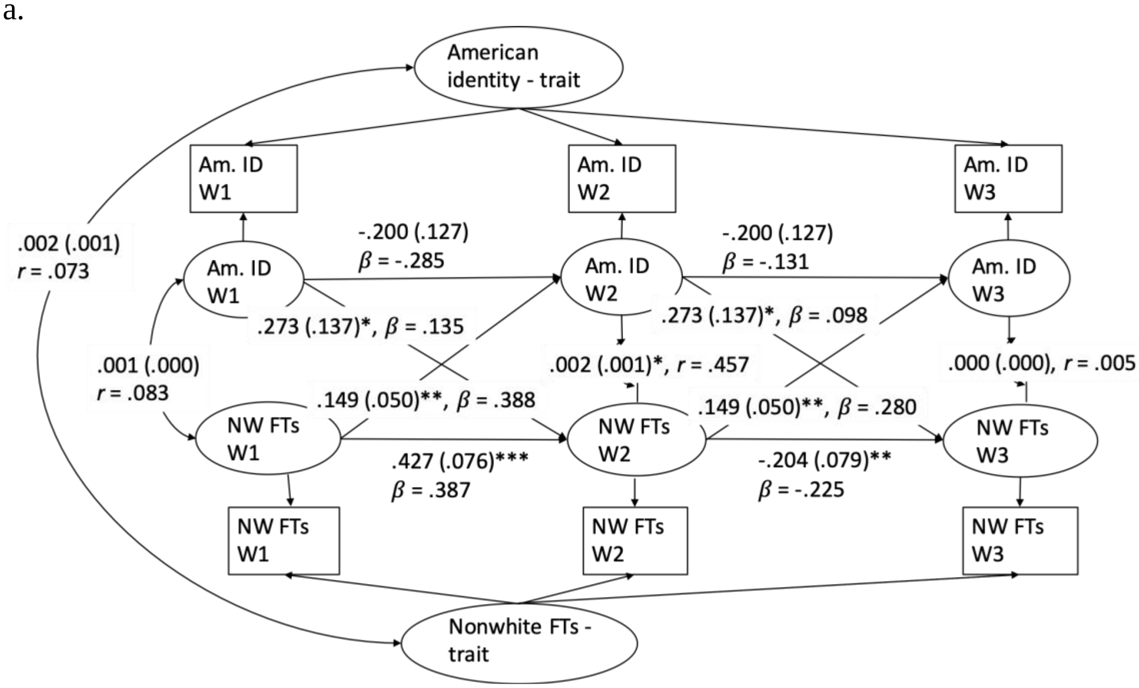


Figure 15. Study 1 RI-CLPM for POC identity and nonwhite stereotypes, with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

In contrast to the lack of between-person effects (i.e., trait-level covariance) and the lack of cross-lagged effects in the CLPM, American identity and nonwhite FT ratings had significant, positive cross-lagged effects at the within-person level in the RI-CLPM (ID-FT: $b = .273$, $SE = .137$, $p = .047$, β = .135 & .098; FT-ID: $b = .149$, $SE = .050$, $p = .003$, β = .388 & .280), though the forward effect is only significant with the stationarity assumption. (The American identity-nonwhite FT RI-CLPM with stationarity is shown in Figure 16a). Thus, although the CLPM and trait-level covariance would suggest that

American identity has no effect on attitudes toward other racial minorities, the RI-CLPM suggests that higher American identity might actually improve at least affective attitudes at the within-person level. However, as can be seen in Figure 16b, American identity did not show the same positive within-person cross-lagged effects on nonwhite stereotype ratings, or at least not consistently across time lags (W1-W2: b = -.532, SE = .269, p = .048, β = -.337; W2-W3: b = .384, SE = .200, p = .056, β = .190). The reverse effect also switched signs (in the opposite direction) across time lags (W1-W2: b = .224, SE = .090, p = .017, β = .384; W2-W3: b = -.197, SE = .097, p = .041, β = -.287).

a.



b.

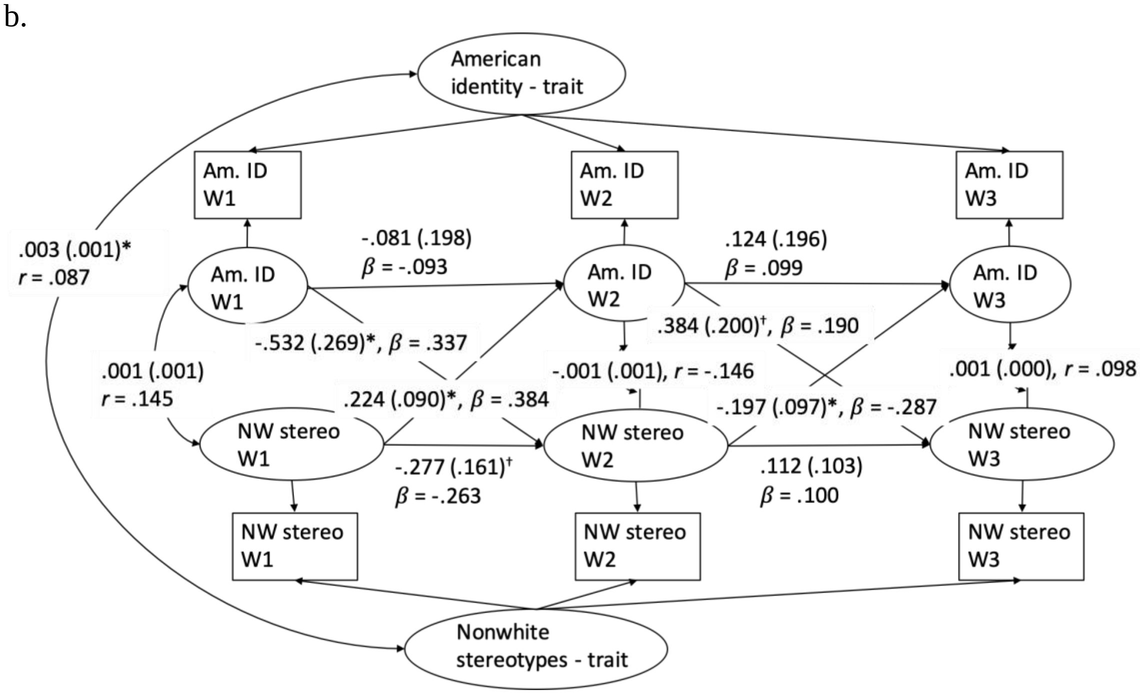


Figure 16. Study 1 RI-CLPM for American identity and nonwhite FTs, with stationarity constraints on lagged and cross-lagged coefficients (a) and American identity and nonwhite stereotypes, with no stationarity constraints (b). Unstandardized coefficients

with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Again, in contrast to the CLPM results and the RI-CLPM between-person results, American identity did not have significant within-person cross-lagged effects on White FT ratings in the RI-CLPM. Furthermore, controlling for positive, trait-level covariance, American identity and White stereotype ratings showed negative cross-lagged effects on each other (ID-stereotype: b = -.400, SE = .136, p = .003, β = -.188 & -.162; stereotype-ID: b = -.082, SE = .031, p = .008, β = -.202 & -.177) in the model with stationarity, as shown in Figure 17. Thus, American identity appears to relate to Asian Americans' racial attitudes differently at the between- and within-person levels.

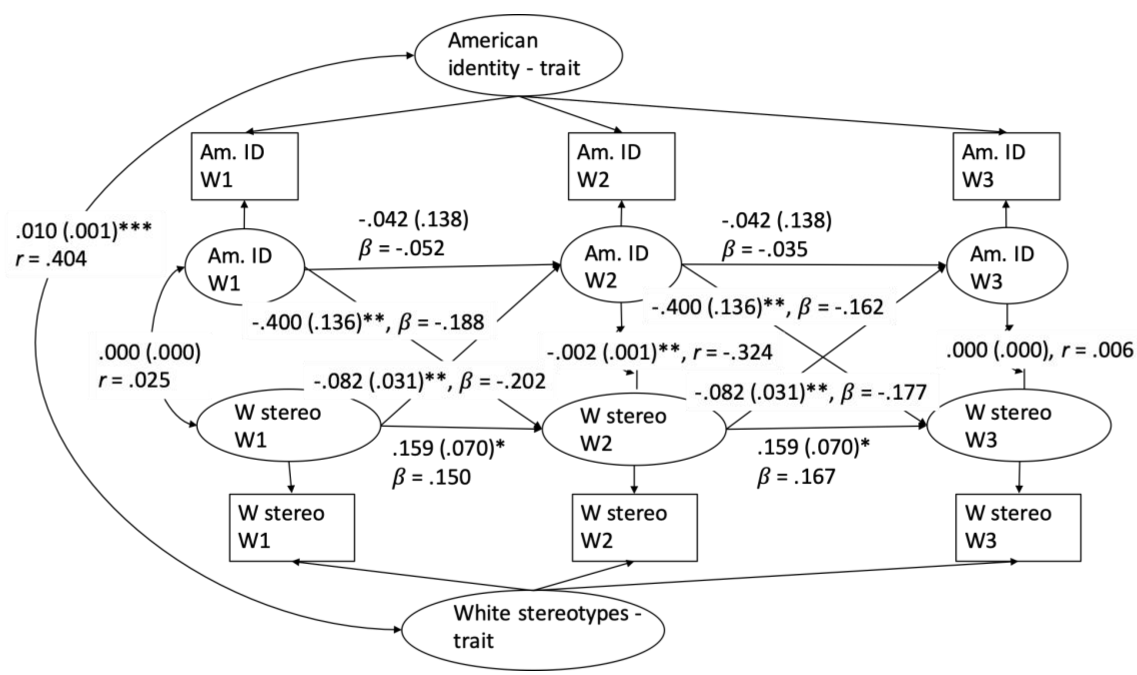


Figure 17. Study 1 RI-CLPM for American identity and White stereotypes, with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Unexpectedly, some significant cross-lagged effects appeared between Asian American identity and attitudes toward Whites in the RI-CLPM. For White FT ratings (Figure 18), both the forward and reverse effects switched signs, in opposite directions, across waves (forward W1-W2: $b = .354$, $SE = .179$, $p = .048$, $\beta = .239$; forward W2-W3: $b = -.254$, $SE = .123$, $p = .039$, $\beta = -.172$; reverse W1-W2: $b = -.256$, $SE = .095$, $p = .007$, $\beta = -.332$; reverse W2-W3: $b = .135$, $SE = .059$, $p = .023$, $\beta = .186$). For White stereotype ratings, the RI-CLPM with stationarity indicated significant, negative cross-lagged effects in both directions (ID-stereotype: $b = -.242$, $SE = .088$, $p = .006$, $\beta = -.171$ & -.142; stereotype-ID: $b = -.136$, $SE = .039$, $p = .001$, $\beta = -.231$ & -.230); however, stationarity significantly worsened model fit, and only the W1-W2 reverse effect was significant in the RI-CLPM without stationarity ($b = -.152$, $SE = .076$, $p = .047$, $\beta = -.217$).

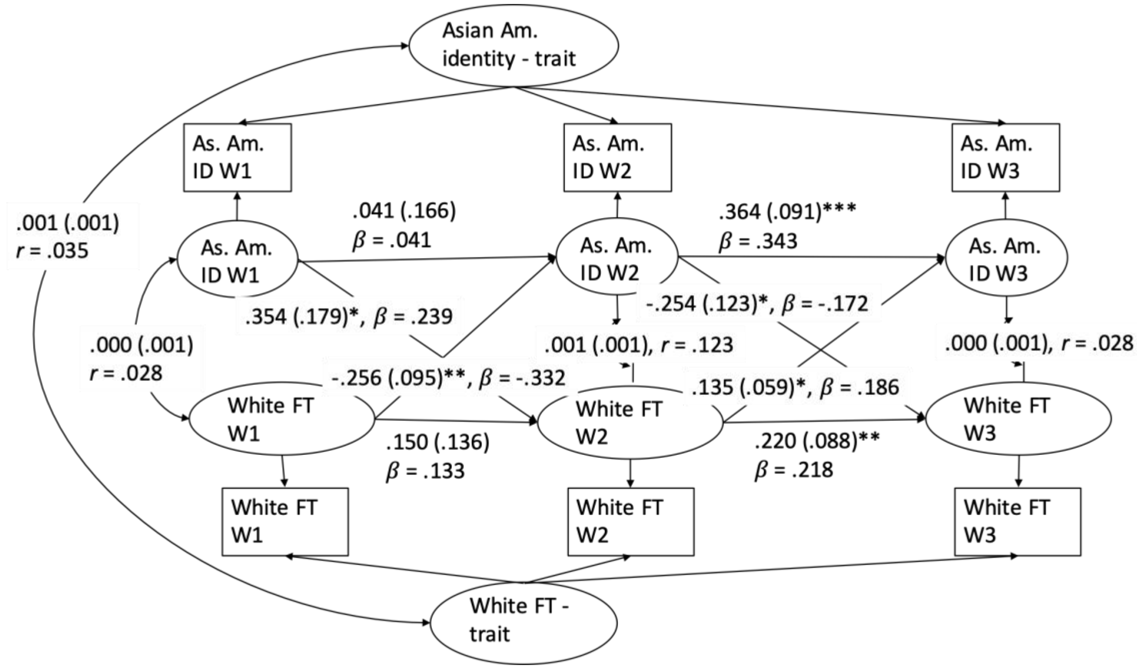


Figure 18. Study 1 RI-CLPM for Asian American identity and the White FT, with no stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Additionally, controlling for the negative trait-level covariance, White FT ratings had a significant, positive cross-lagged effect on POC identity ($b = .138$, $SE = .067$, $p = .040$, β = .187 & .165) in the RI-CLPM (Figure 19). This finding further suggests that identity and racial attitudes might relate to each other differently at the between- and within-person levels.

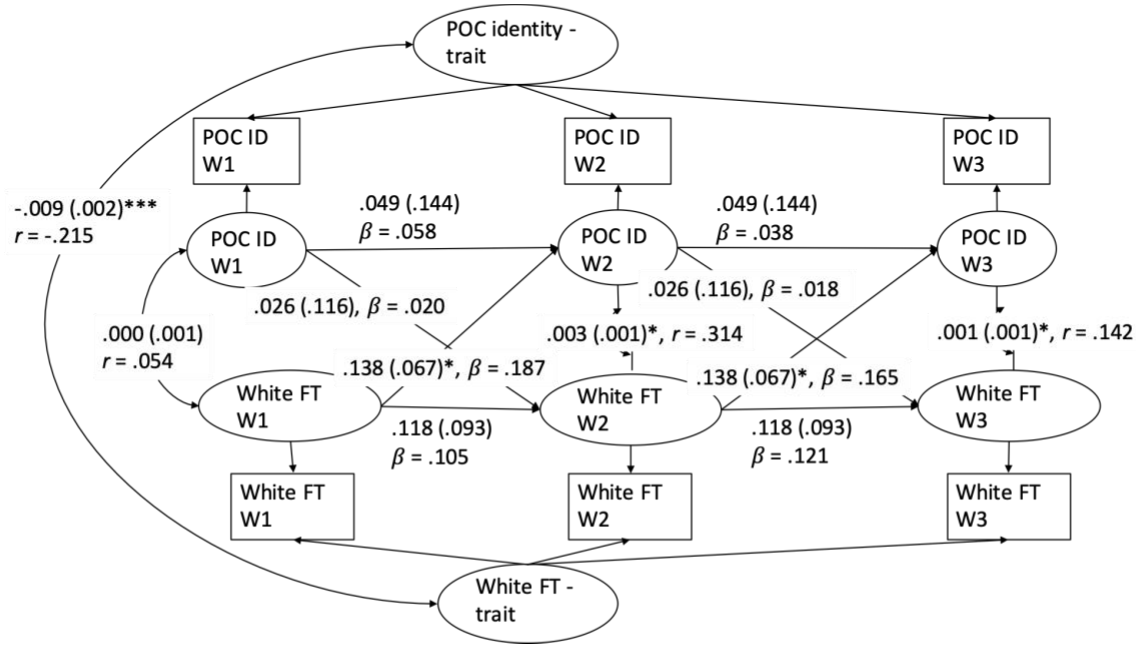


Figure 19. Study 1 RI-CLPM for POC identity and the White FT, with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

4. Identity and Policy Attitudes

a. Immigration. In my hypotheses, I treated immigration as an own-group issue area for Asian Americans. Thus, I expected Asian American identity to predict more liberal immigration policy stances—allowing more immigrants and opposing deportation and detention of undocumented immigrants—which would be captured by higher immigration attitude factor scores (Hypothesis 11). Based on the paradoxical effects literature, I expected American identity to predict less liberal immigration attitudes (i.e., lower immigration attitude factor scores) (Hypothesis 13). I did not expect POC identity to predict immigration attitudes.

Several of the panel models did not initially converge, but setting starting values in those models resulted in all CLPM converging. Starting values were based on OLS regressions of each Wave 2 variable on all Wave 1 variables and each Wave 3 variable on all Wave 2 variables for models without stationarity and based on coefficients from the model that did not converge for models with stationarity. The final CLPM models did not show adequate fit based on CFI (ranging from .81 for Asian American identity without covariates to .85 for American identity with covariates) or RMSEA (ranging from .55 for POC identity without covariates and with stationarity to .83 for American identity with covariates and age of arrival in U.S. and no stationarity), but they did meet fit criteria for SRMR (all SRMR < .03). Fit statistics are presented in Table 19. Stationarity had a marginally significant effect on model fit for Asian American identity without covariates ($\chi^2_8 = 1573.103, \chi^2_4 = 1565.120, \Delta\chi^2_4 = 7.983, p = .092$) but did not significantly affect fit for any other CLPM model.[9]

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[9] Thus, coefficients reported in the text are from the CLPM with stationarity unless otherwise specified.

Table 19

Study 1 Panel Model Fit Statistics: Immigration Attitudes

	N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Asian American ID						
CLPM Model 1	630	.812	.787	.021	1565.120 (4)***	
CLPM Model 1 w/ stationarity	630	.811	.557	.026	1573.103 (8)***	7.983 (4)[†]
CLPM Model 2	612	.839	.790	.008	1533.409 (4)***	
CLPM Model 2 w/ stationarity	612	.839	.560	.010	1541.115 (8)***	7.706 (4)
CLPM Model 3	124	.841	.808	.007	327.692 (4)***	
CLPM Model 3 w/ stationarity	124	.839	.574	.013	335.100 (8)***	7.408 (4)
RI-CLPM	630	1.000	.000	.002	0.103 (1)	1565.017 (3)***
RI-CLPM w/ stationarity[a]	630	.999	.048	.026	12.244 (5)*	12.141 (4)*
IV: POC ID						
CLPM Model 1	630	.824	.783	.014	1547.994 (4)***	
CLPM Model 1 w/ stationarity	630	.824	.553	.017	1550.767 (8)***	2.773 (4)
CLPM Model 2	612	.848	.787	.005	1520.744 (4)***	
CLPM Model 2 w/ stationarity	612	.848	.556	.006	1523.004 (8)***	2.260 (4)
CLPM Model 3	124	.847	.800	.005	321.548 (4)***	
CLPM Model 3 w/ stationarity	124	.847	.565	.007	324.771 (8)***	3.223 (4)
RI-CLPM	630	1.000	.000	.006	0.910 (1)	1547.084 (3)***
RI-CLPM w/ stationarity	630	1.000	.022	.012	6.471 (5)	5.561 (4)
IV: American ID						
CLPM Model 1	630	.825	.797	.014	1603.925 (4)***	
CLPM Model 1 w/ stationarity	630	.825	.563	.016	1607.563 (8)***	3.638 (4)
CLPM Model 2	612	.850	.797	.005	1558.587 (4)***	
CLPM Model 2 w/ stationarity	612	.850	.564	.005	1563.083 (8)***	4.496 (4)
CLPM Model 3	124	.850	.827	.004	343.426 (4)***	
CLPM Model 3 w/ stationarity	124	.850	.584	.006	346.786 (8)***	3.360 (4)

RI-CLPM	630	1.000	.019	.005	1.227 (1)	1602.698 (3)***
RI-CLPM w/ stationarity[b]	630	1.000	.000	.006	2.276 (5)	1.049 (4)

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Note: All Asian American identity CLPM and POC identity CLPM Model 2 (with and without stationarity) only converged with starting values for structural coefficients. In models without stationarity, starting values came from ordinary least-squares regression of each W2 variable on all W1 variables and covariates and/or each W3 variable on all W2 variables and covariates; in models with stationarity, starting values came from the CLPM models that did not converge (which produced estimates of coefficients but not standard errors).

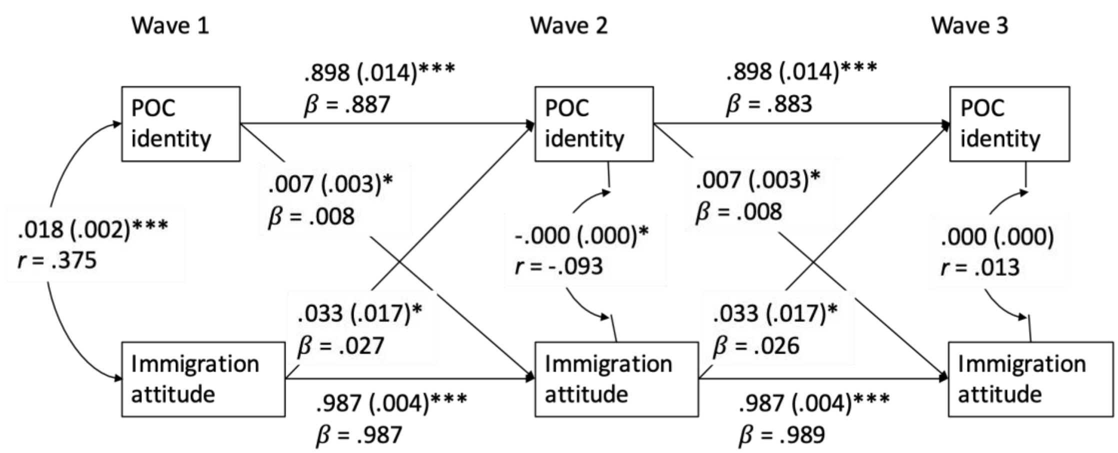
Note: RI-CLPM with stationarity for all 3 identities included a non-significant negative residual variance for the Wave 3 immigration attitude variable. RI-CLPM without stationarity for Asian American identity also included a non-significant negative residual variance for this variable. Constraining this residual variance to 0 resulted in the Asian American model without stationarity and the POC identity model with stationarity not converging, and it produced a warning that the covariance matrix of latent variables was not positive definite and an infinite standardized correlation between the Wave 3 identity and immigration variables for the Asian American and American identity models with stationarity.

[a] Asian American identity RI-CLPM with stationarity and Wave 3 immigration attitude residual variance = 0: CFI = .999, RMSEA = .041, SRMR = .026, χ^2_6 = 12.505, $\Delta\chi^2_5$ = 12.402, p = .030.
[b] American identity RI-CLPM with stationarity and Wave 3 immigration attitude residual variance = 0: CFI = 1.000, RMSEA = .000, SRMR = .006, χ^2_6 = 2.281, $\Delta\chi^2_5$ = 1.054, p = .958.

RI-CLPM models converged, but almost all had a non-significant negative residual variance for the Wave 3 immigration latent variable. Only POC identity and American identity without stationarity did not produce this negative variance. Nonetheless, model fit was good for all RI-CLPM models (CFI ≥ .999, RMSEA ≤ .048, SRMR ≤ .026), and RI-CLPM produced significantly better fit than CLPM in every case (see Table 18). Stationarity significantly worsened model fit for Asian American identity ($\chi^2_5 = 12.244, \chi^2_1 = 0.103, \Delta\chi^2_4 = 12.141, p = .016$) but not for POC or American identity. Constraining the Wave 3 immigration residual variance to equal 0 (to eliminate the non-significant negative variance) resulted in the Asian American identity model without stationarity and the POC identity model with stationarity not converging. The Asian American identity and American identity models with stationarity and this variance constraint converged, but with a warning that the covariance matrix of latent variables was not positive definite and an infinite standardized correlation between the Wave 3 identity and immigration variables. This version of the Asian American identity model with stationarity also fit less well than the model without stationarity (with the negative residual variance) ($\chi^2_6 = 12.505, \chi^2_1 = 0.103, \Delta\chi^2_5 = 12.402, p = .030$). Because of the worse model fit for Asian American identity and the problems with the Wave 3 immigration variance for POC and American identities when stationarity was assumed, RI-CLPM coefficients reported below are from the models without stationarity unless otherwise specified.

All three identities had significant trait-level covariance with immigration attitudes. Consistent with my hypotheses, this covariance was positive for Asian American identity (*c* = .005, *SE* = .001, *p* = .001, *r* = .142) and negative for American identity (c = -.007, SE = .002, p < .001, r = -.200). However, POC identity also had a significant, positive trait-level covariance with immigration attitudes that was, if anything, larger than the covariance between Asian American identity and immigration attitudes (c = .018, SE = .002, p < .001, r = .391).

Cross-lagged effects from Asian American and American identities to immigration attitudes were not significant in either the CLPM or RI-CLPM, though a significant reverse effect from immigration attitudes to American identity appeared in the CLPM (b = -.023, SE = .011, p = .030, β = -.024). Again, though I did not predict them, there were significant cross-lagged effects in the CLPM (with stationarity) for POC identity and immigration attitudes (ID to attitude: b = .007, SE = .003, p = .040, β = .008; attitude to ID: b = .033, SE = .017, p = .047, β = .027 & .026) (Figure 20).[10] Cross-lagged coefficients were not significant for any identity in the RI-CLPM.



[10] Although stationarity did not significantly affect model fit, the only significant cross-lagged coefficient in the model without stationarity was from Wave 2 identity to Wave 3 immigration attitude (b = .009, SE = .004, p = .032, β = .011).

Figure 20. Study 1 CLPM for POC identity and immigration attitudes, without covariates and with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

These results suggest that identities and attitudes are related at the between-person level, and the signs of these relationships are consistent with the literature on collective action/group consciousness and paradoxical effects of prejudice reduction. However, I did not find evidence that Asian American or American identity precedes immigration attitudes either between or within individuals. On the other hand, the results suggest that Asian American individuals who identify more strongly as POC might shift toward more liberal immigration attitudes compared to those who identify less strongly as POC.

b. Criminal justice reform. I treated criminal justice reform as an other-group issue for Asian Americans. Thus, I hypothesized that POC identity would predict more support for criminal justice reform—belief that there are too many people in prison and support for defunding police and eliminating mandatory minimum sentences—which would be captured by higher criminal justice factor scores (Hypothesis 12) and that American identity would predict less support for criminal justice reform (i.e., lower criminal justice factor scores) (Hypothesis 13). I did not expect Asian American identity to predict attitudes toward criminal justice reform.

I fit panel models for two different versions of criminal justice factor scores: one that treated all three items as continuous variables and one that treated the number of people in prison item as an ordered categorical variable (too few < about the right number < too many). Fit statistics are presented in Tables 20 (continuous variable models) and 21 (categorical variable models). However, with the ordered categorical variable, starting values (from OLS regression) were needed for the CLPM models with POC and American identities and age of arrival in the U.S. to converge, the RI-CLPM models with stationarity had (non-significant) negative residual variances for the Wave 2 criminal justice attitude latent variable, and the RI-CLPM models without stationarity did not converge. Fixing the residual variance for the Wave 2 criminal justice attitude latent variable to 0 allowed the models for Asian American and POC identities to converge but (in models with and without stationarity) produced warnings that the covariance matrix of latent variables was not positive definite, as well as infinite standardized correlation coefficients for the Wave 2 identity and criminal justice attitude variables; the same warning and infinite standardized correlation coefficient occurred when I fixed this residual variance in the American identity model with stationarity.[11] The RI-CLPM without stationarity for American identity did not converge with this variance set to 0. With either set of factor scores, CLPM models fit well based on CFI (all ≥ .966) and SRMR (all ≤ .026) but not RMSEA (.118 for the categorical variable with POC identity, age of arrival in the U.S., and stationarity, to .307 for the continuous variable with American identity, age of arrival in the U.S., and no stationarity). Stationarity did not significantly affect fit for any of the CLPM models, but it significantly worsened the fit of the RI-CLPM for Asian American identity (continuous variable factor scores: $\chi^2_5 =$

[11] RI-CLPM fit statistics in Table 21 are reported for the models with the Wave 2 criminal justice residual variance set to 0.

$13.622, \chi_1^2 = 0.204, \Delta\chi_4^2 = 13.418, p = .009$; categorical variable factor scores: $\chi_6^2 = 16.088, \chi_2^2 = 1.328, \Delta\chi_4^2 = 14.760, p = .005$). Thus, CLPM coefficients reported below are from the models with stationarity, RI-CLPM coefficients for POC and American identities are from models with stationarity (and with the Wave 2 criminal justice residual variance fixed to 0 when categorical variable factor scores were used), and RI-CLPM coefficients for Asian American identity are from models without stationarity (and with the fixed residual variance when categorical variable factor scores were used). When RI-CLPM models converged without negative variances (i.e., with continuous variable factor scores), they fit significantly better than their corresponding CLPM models.[12]

[12] The fit of the CLPM was not compared to the fit of the RI-CLPM with the Wave 2 criminal justice residual variance set to 0 because the CLPM is not nested within this version of the RI-CLPM.

Table 20

Study 1 Panel Model Fit Statistics: Criminal Justice Attitudes (continuous indicators)

	N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Asian American ID						
CLPM Model 1	628	.969	.263	.021	178.205 (4)***	
CLPM Model 1 w/ stationarity	628	.968	.188	.026	185.011 (8)***	6.806 (4)
CLPM Model 2	610	.976	.255	.008	162.157 (4)***	
CLPM Model 2 w/ stationarity	610	.976	.182	.010	168.900 (8)***	6.743 (4)
CLPM Model 3	125	.975	.275	.007	41.825 (4)***	
CLPM Model 3 w/ stationarity	125	.976	.192	.011	45.026 (8)***	3.201 (4)
RI-CLPM	628	1.000	.000	.003	0.204 (1)	178.001 (3)***
RI-CLPM w/ stationarity	628	.998	.052	.026	13.622 (5)*	13.418 (4)**
IV: POC ID						
CLPM Model 1	628	.973	.253	.015	165.301 (4)***	
CLPM Model 1 w/ stationarity	628	.973	.179	.017	169.382 (8)***	4.081 (4)
CLPM Model 2	610	.979	.245	.005	150.895 (4)***	
CLPM Model 2 w/ stationarity	610	.980	.173	.006	153.835 (8)***	2.940 (4)
CLPM Model 3	125	.980	.248	.005	34.797 (4)***	
CLPM Model 3 w/ stationarity	125	.982	.168	.007	36.298 (8)***	1.501 (4)
RI-CLPM	628	1.000	.021	.006	1.265 (1)	164.036 (3)***
RI-CLPM w/ stationarity	628	1.000	.000	.011	4.548 (5)	3.283 (4)
IV: American ID						
CLPM Model 1	628	.966	.293	.014	219.779 (4)***	
CLPM Model 1 w/ stationarity	628	.966	.208	.018	226.135 (8)***	6.356 (4)
CLPM Model 2	610	.975	.278	.005	192.818 (4)***	
CLPM Model 2 w/ stationarity	610	.975	.196	.005	195.345 (8)***	2.527 (4)
CLPM Model 3	125	.973	.307	.004	51.214 (4)***	
CLPM Model 3 w/ stationarity	125	.974	.215	.006	54.333 (8)***	3.119 (4)

RI-CLPM	628	1.000	.000	.001	0.037 (1)	219.742 (3)***
RI-CLPM w/ stationarity	628	1.000	.000	.005	1.980 (5)	1.943 (4)

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 21

Study 1 Panel Model Fit Statistics: Criminal Justice Attitudes (categorical indicator)

	N	**CFI**	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
IV: Asian American ID						
CLPM Model 1	628	.981	.231	.021	138.253 (4)***	
CLPM Model 1 w/ stationarity	628	.980	.165	.026	145.220 (8)***	6.967 (4)
CLPM Model 2	610	.985	.225	.008	127.337 (4)***	
CLPM Model 2 w/ stationarity	610	.985	.160	.009	133.234 (8)***	5.897 (4)
CLPM Model 3	125	.986	.224	.007	28.987 (4)***	
CLPM Model 3 w/ stationarity	125	.987	.154	.011	31.812 (8)***	2.825 (4)
RI-CLPM	628	1.000	.000	.006	1.328 (2)	
RI-CLPM w/ stationarity	628	.999	.052	.026	16.088 (6)*	14.760 (4)**
IV: POC ID						
CLPM Model 1	628	.984	.220	.014	125.364 (4)***	
CLPM Model 1 w/ stationarity	628	.984	.155	.016	128.816 (8)***	3.452 (4)
CLPM Model 2	610	.987	.214	.005	115.953 (4)***	
CLPM Model 2 w/ stationarity	610	.987	.150	.006	117.841 (8)***	1.888 (4)
CLPM Model 3	125	.991	.182	.005	20.473 (4)***	
CLPM Model 3 w/ stationarity	125	.992	.118	.007	21.981 (8)***	1.508 (4)
RI-CLPM	628	1.000	.012	.006	2.196 (2)	

RI-CLPM w/ stationarity	628	1.000	.013	.009	6.615 (6)	4.419 (4)
IV: American ID						
CLPM Model 1	628	.978	.264	.014	179.084 (4)***	
CLPM Model 1 w/ stationarity	628	.978	.187	.017	184.074 (8)***	4.990 (4)
CLPM Model 2	610	.983	.250	.005	157.105 (4)***	
CLPM Model 2 w/ stationarity	610	.983	.176	.005	159.020 (8)***	1.915 (4)
CLPM Model 3	125	.983	.260	.004	37.830 (4)***	
CLPM Model 3 w/ stationarity	125	.984	.179	.005	40.092 (8)***	2.262 (4)
RI-CLPM	628					
RI-CLPM w/ stationarity	628	1.000	.000	.006	5.043 (6)	

Note: POC identity CLPM Model 2 without stationarity and American identity Model 3 without stationarity only converged with starting values for structural coefficients. Starting values came from ordinary least-squares regression of each W2 variable on all W1 variables and covariates and each W3 variable on all W2 variables and covariates.

Note: RI-CLPM without stationarity did not initially converge. RI-CLPM with stationarity converged, but included a non-significant negative residual variance for the Wave 2 criminal justice attitude variable. Setting the Wave 2 criminal justice residual variance to 0 allowed the RI-CLPM without stationarity for Asian American and POC identities to converge with a warning that the covariance matrix of latent variables was not positive definite, as well as infinite standardized correlation coefficients for the Wave 2 identity and criminal justice attitude variables. Setting these residual variances to 0 produced similar warnings and infinite correlations for the RI-CLPM with stationarity for all 3 identities. For ease of comparison between models with and without stationarity, fit statistics reported in the table are from the RI-CLPM with the Wave 2 criminal justice residual variance set to 0.

Criminal justice attitudes had significant, positive trait-level covariance with POC identity (continuous variable factor scores: $c = .010$, $SE = .002$, $p < .001$, $r = .216$; categorical variable factor scores: $c = .012$, $SE = .002$, $p < .001$, $r = .245$ and significant, negative trait-level covariance with American identity (continuous variable factor scores: $c = -.003$, $SE = .002$, $p = .034$, $r = -.087$; categorical variable factor scores: $c = -.005$, $SE = .002$, $p = .003$, $r = -.120$) in the RI-CLPM. The signs of these covariances are consistent with my hypotheses. Also consistent with my hypotheses, Asian American identity did not have a significant trait-level covariance with criminal justice attitudes (continuous variable factor scores: $c = .000$, $SE = .002$, $p = .792$, $r = .011$; categorical variable factor scores: $c = .000$, $SE = .002$, $p = .830$, $r = .009$).

Cross-lagged coefficients were not significant across most models. However, the RI-CLPM with POC identity and categorical variable criminal justice factor scores (Figure 21) had significant, negative cross-lagged effects in both directions (ID to attitude: $b = -.068$, $SE = .032$, $p = .033$, W1-W2 $\beta = -.761$, W2-W3 $\beta = -.227$; attitude to ID: $b = -1.166$, $SE = .529$, $p = .028$, W1-W2 $\beta = -.277$, W2-W3 $\beta = -.091$). These negative cross-lagged coefficients contrast with the positive trait-level covariance and potentially contradict my hypothesis that higher POC identification predicts increased support for criminal justice reform. But the model fitting problems for the RI-CLPM with the criminal justice factor scores treating the number of people in prison item as categorical cautions against over-interpreting this result.

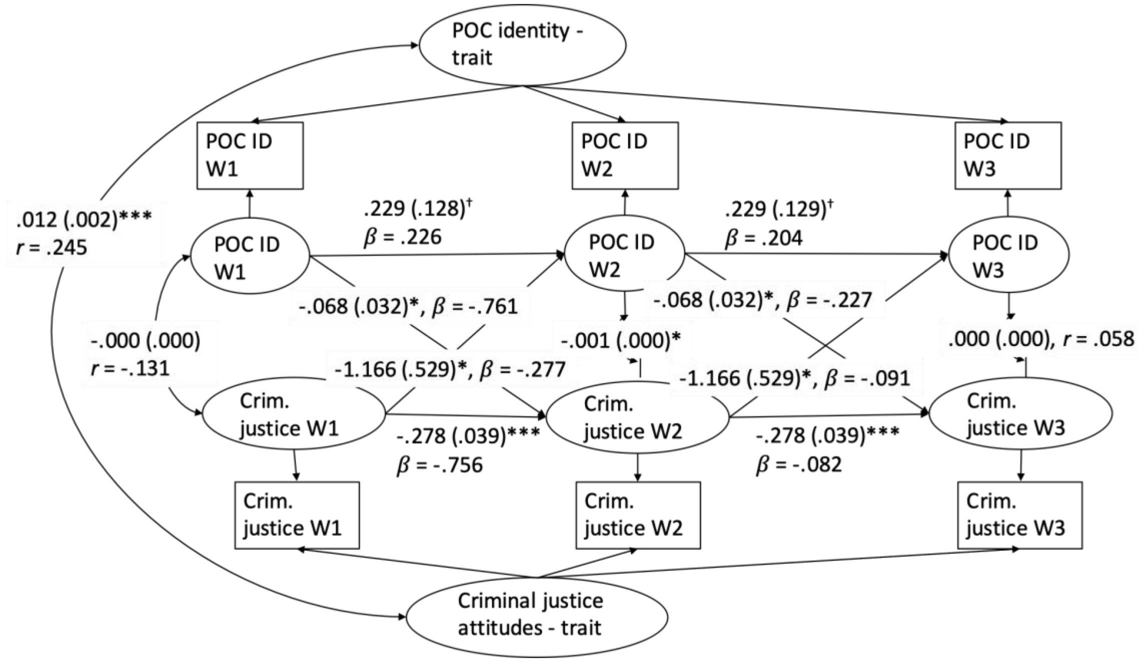


Figure 21. Study 1 RI-CLPM for POC identity and criminal justice attitudes (factor scores from the CFA model treating the number of people in prison item as categorical), with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. (Identity-attitude correlation coefficient for Wave 2 is not shown because it was estimated as -∞.) Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

c. Affirmative action. Because of its status as a wedge issue between some Asian Americans and other racial minority groups, I treated affirmative action as an other-group issue area even though Asian Americans might benefit from it. Thus, as with criminal justice reform, I hypothesized that POC identity would predict more support (Hypothesis 12) and American identity would predict less support (Hypothesis 13) for affirmative action, and I did not expect Asian American identity to predict affirmative action attitudes.

In contrast to immigration and criminal justice reform, all CLPM and RI-CLPM models for affirmative action attitudes converged without issue. CLPM models without covariates were slightly below the CFI criterion for good fit (.934-.936 for Asian American identity, .946-.949 for POC identity, and .939-.940 for American identity), but the models with covariates met this criterion. All CLPM models met the SRMR criterion (all ≤ .041), but none met the RMSEA criterion (.177 for POC identity with age of arrival in U.S. and stationarity to .311 for American identity without covariates or stationarity). All RI-CLPM models fit well (CFI ≤ .997, RMSEA ≤ .055, SRMR ≤ .031), and showed significantly improved fit over CLPM. Stationarity significantly worsened CLPM fit for POC identity ($\chi^2_8 = 212.368, \chi^2_4 = 198.373, \Delta\chi^2_4 = 13.995, p =$ .007) and American identity ($\chi^2_8 = 259.858, \chi^2_4 = 248.532, \Delta\chi^2_4 = 11.326, p =$ .023) and marginally significantly worsened CLPM fit for Asian American identity ($\chi^2_8 = 222.405, \chi^2_4 = 214.542, \Delta\chi^2_4 = 7.863, p =$ .097).[13] With RI-CLPM, stationarity significantly affected fit only for Asian American identity ($\chi^2_5 = 14.321, \chi^2_1 = 0.766, \Delta\chi^2_4 = 13.555, p =$ .009). Fit statistics are presented in Table 22.

[13] Stationarity also resulted in significantly worse fit for POC identity and marginally significantly worse fit for Asian American identity with the foreign-born covariate (see Table 22).

Table 22

Study 1 Panel Model Fit Statistics: Affirmative Action Attitudes

	N	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Asian American ID						
CLPM Model 1	632	.936	.289	.037	214.542 (4)***	
CLPM Model 1 w/ stationarity	632	.934	.206	.041	222.405 (8)***	7.863 (4)†
CLPM Model 2	614	.960	.270	.012	183.477 (4)***	
CLPM Model 2 w/ stationarity	614	.959	.193	.014	191.728 (8)***	8.251 (4)†
CLPM Model 3	126	.959	.273	.014	41.597 (4)***	
CLPM Model 3 w/ stationarity	126	.959	.194	.017	45.918 (8)***	4.321 (4)
RI-CLPM	632	1.000	.000	.005	0.766 (1)	213.776 (3)***
RI-CLPM w/ stationarity	632	.997	.054	.031	14.321 (5)*	13.555 (4)**
IV: POC ID						
CLPM Model 1	632	.949	.277	.033	198.373 (4)***	
CLPM Model 1 w/ stationarity	632	.946	.201	.037	212.368 (8)***	13.995 (4)**
CLPM Model 2	614	.966	.261	.011	170.880 (4)***	
CLPM Model 2 w/ stationarity	614	.964	.189	.012	184.177 (8)***	13.297 (4)**
CLPM Model 3	126	.967	.253	.014	36.218 (4)***	
CLPM Model 3 w/ stationarity	126	.968	.177	.016	39.517 (8)***	3.299 (4)
RI-CLPM	632	.999	.055	.010	2.916 (1)†	195.457 (3)***
RI-CLPM w/ stationarity	632	.999	.028	.016	7.470 (5)	4.554 (4)
IV: American ID						
CLPM Model 1	632	.940	.311	.033	248.532 (4)***	
CLPM Model 1 w/ stationarity	632	.939	.223	.037	259.858 (8)***	11.326 (4)*
CLPM Model 2	614	.962	.287	.011	205.785 (4)***	
CLPM Model 2 w/ stationarity	614	.962	.203	.011	210.575 (8)***	4.790 (4)
CLPM Model 3	126	.965	.284	.012	44.688 (4)***	
CLPM Model 3 w/ stationarity	126	.965	.200	.014	48.148 (8)***	3.460 (4)

RI-CLPM	632	1.000	.033	.008	1.700 (1)	246.832 (3)***
RI-CLPM w/ stationarity	632	.999	.026	.016	7.171 (5)	5.471 (4)

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Again, consistent with my hypotheses, POC identity had a significant, positive trait-level covariance (c = .025, SE = .003, p < .001, r = .431), and American identity had a significant, negative trait-level covariance (c = -.006, SE = .002, p = .004, r = -.123) with support for affirmative action (estimates from models with stationarity). But Asian American identity also had a significant, positive trait-level covariance with support for affirmative action (without stationarity: c = .005, SE = .002, p = .012, r = .116).

CLPM showed significant, positive cross-lagged effects in both directions for POC identity, at least from Wave 1 to Wave 2 (ID-attitude: b = .114, SE = .029, p < .001, β = .100; attitude-ID: b = .062, SE = .017, p < .001, β = .071) in the model without stationarity (Figure 22). Thus, respondents who identified more as POC in Wave 1 showed increased support for affirmative action from Wave 1 to Wave 2 compared to respondents who identified less as POC, and respondents who reported more support for affirmative action in Wave 1 showed increased identification as POC from Wave 1 to Wave 2 compared to respondents who reported less support for affirmative action. Although the Wave 2 to Wave 3 coefficients remain positive, however, they are not significant, and the stationarity assumption does not hold, which suggests that these effects are not the same across both time lags.

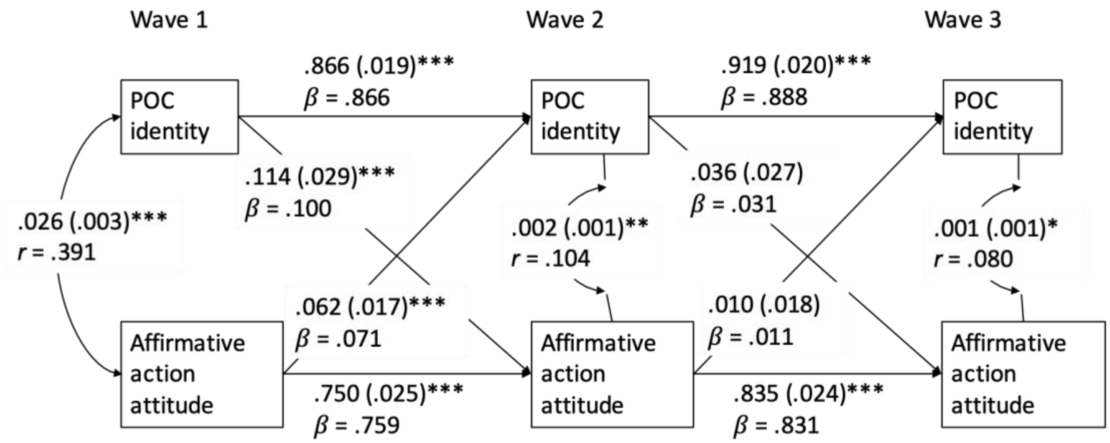


Figure 22. Study 1 CLPM without covariates and with no stationarity constraints for POC identity and affirmative action attitudes. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Unexpectedly, Asian American identity showed a similar pattern of results to POC identity, at least in the model with stationarity (Figure 23), though the cross-lagged effects are only marginally significant (ID-attitude: $b = .042$, $SE = .024$, $p = .076$, $\beta = .027$; attitude-ID: $b = .018$, $SE = .010$, $p = .069$, $\beta = .026$).

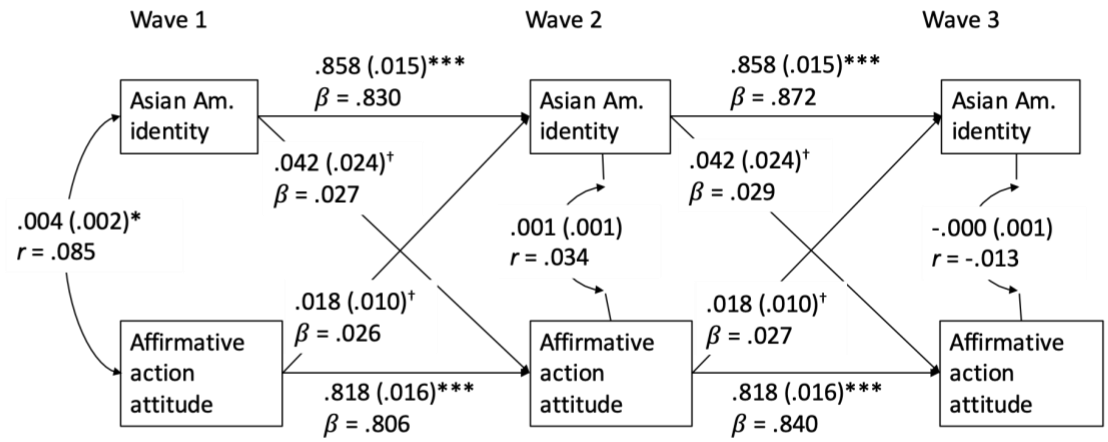


Figure 23. Study 1 CLPM without covariates and with stationarity constraints on lagged and cross-lagged coefficients for Asian American identity and affirmative action attitudes. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

By contrast, cross-lagged effects from American identity to affirmative action attitudes were not significant in the CLPM. However, the reverse effect from affirmative action attitude to American identity was significant from Wave 2 to Wave 3 ($b = -.024$, $SE = .011$, $p = .022$, $\beta = -.034$) in the model without stationarity.

At the within-person level, RI-CLPM (with stationarity) (Figure 24) revealed significant, positive cross-lagged effects in both directions for POC identity and affirmative action attitudes (ID-attitude: $b = .364$, $SE = .116$, $p = .002$, $\beta = .280$ & $.256$; attitude-ID: $b = .107$, $SE = .049$, $p = .030$, $\beta = .169$ & $.127$), consistent with the effects in the CLPM. However, controlling for the negative trait-level covariance, American identity also had a significant, positive cross-lagged effect on affirmative action attitudes

(b = .439, SE = .177, p = .013, β = .224 & .244), and affirmative action attitudes had a marginally significant, positive cross-lagged effect on American identity (b = .070, SE = .036, p = .052, β = .166 & .141) in the RI-CLPM with stationarity (Figure 25). Asian American identity in Wave 2 had a marginally significant, positive cross-lagged effect on affirmative action attitudes in Wave 3 (b = .291, SE = .173, p = .094, β = .189) in the RI-CLPM without stationarity (Figure 26). Thus, while POC identity and, to some extent, Asian American identity appear to be related to affirmative action attitudes similarly at the between- and within-person levels, American identity appears to be negatively related to affirmative action attitudes at the between-person level but (contrary to Hypothesis 13) positively related at the within-person level.

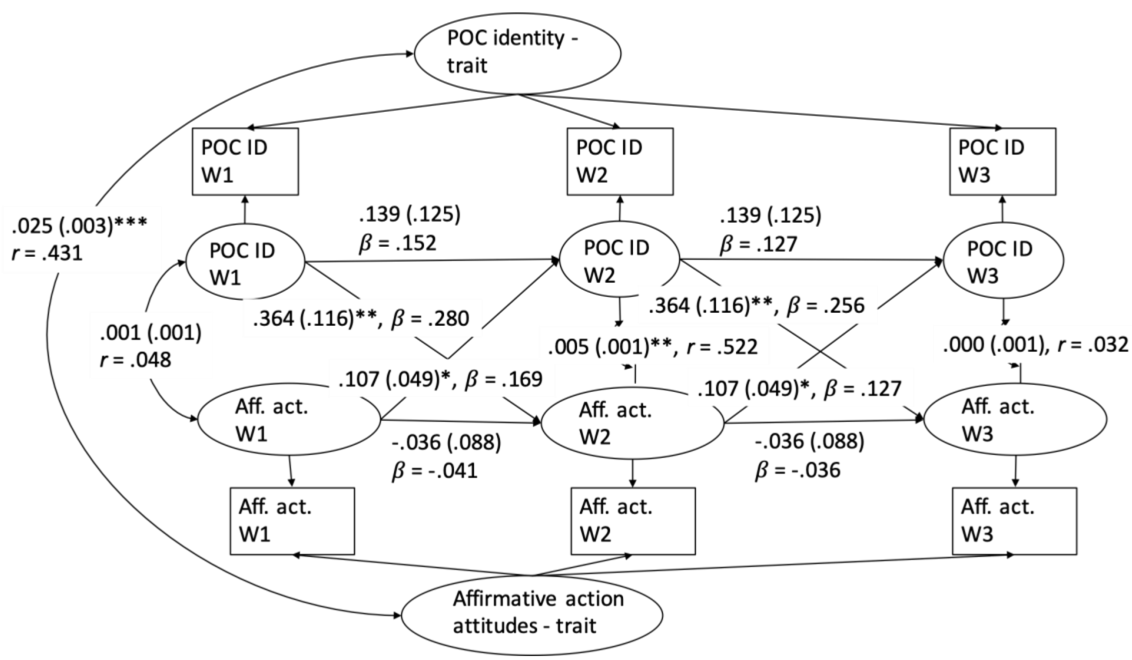


Figure 24. Study 1 RI-CLPM with stationarity constraints on lagged and cross-lagged coefficients for POC identity and affirmative action attitudes. Unstandardized coefficients

with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

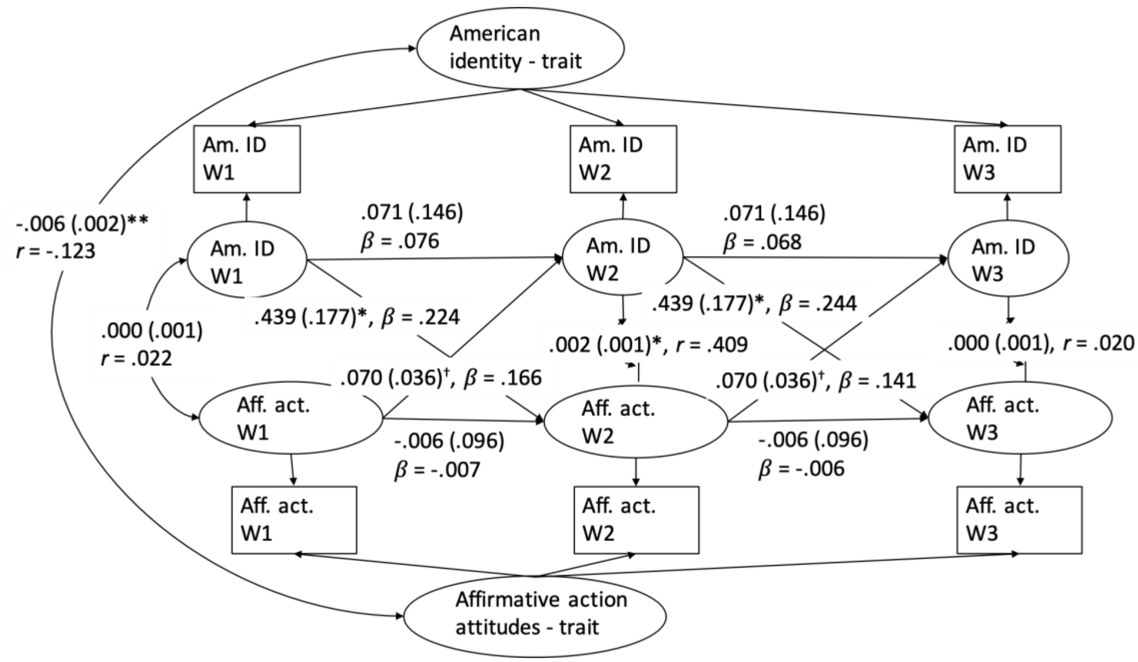


Figure 25. Study 1 RI-CLPM for American identity and affirmative action attitudes, with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

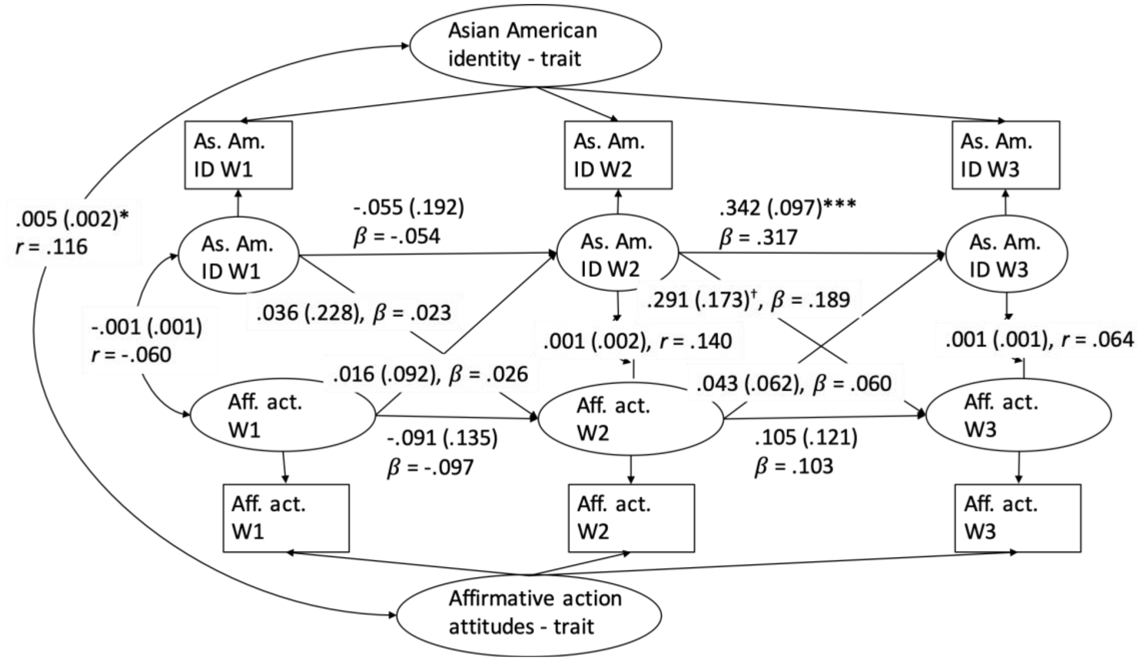


Figure 26. Study 1 RI-CLPM with no stationarity constraints for Asian American identity and affirmative action attitudes. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

5. Identity-Policy Attitude Indirect Effects

Although the cross-lagged effects of Asian American, POC, and American identities on policy attitudes were generally not significant, I examined whether they nevertheless had indirect effects through each of the four mediator factors scores generated from the longitudinal CFA models: efficacy, linked fate, perceived discrimination, and relative deprivation. For each combination of identity, mediator, and policy attitude, I first fit a full model with lagged or cross-lagged paths from each variable to every variable in the next wave and covariances or residual covariances among all three variables within each wave. I then fit a model with stationarity across time lags (i.e., constraining lagged and cross-lagged paths from Wave 2 to Wave 3 to be equal to their counterparts from Wave 1 to Wave 2) and a directional model with only forward structural paths (in other words, all reverse paths—mediator to identity, attitude to mediator, attitude to identity—were set to 0). For immigration attitudes, model fit was generally poor based on CFI (≤ .855) and RMSEA (≥ .520 for full models) but acceptable based on SRMR (≤ .041 for full models, ≤ .055 for all models). For criminal justice reform attitudes,[14] SRMR indicated good fit (≤ .049), and CFI indicated good fit (> .95) except where efficacy was the mediator (CFI = .924-.939), but RMSEA still failed to meet the criteria for acceptable fit (≥ .151 for full models). Similarly, for affirmative action, SRMR indicated good fit (≤ .056), CFI was mixed but lowest for models with efficacy (CFI = .875-.904 efficacy; CFI = .930-.969 other mediators), and RMSEA again indicated poor fit (≥ .172 for full models). In almost every case, the stationarity and directional models fit significantly less well than the full model, and thus, unless otherwise specified, I report results from the full model. Fit statistics for longitudinal mediation models are presented in Tables 23-25.

[14] To avoid convergence issues, mediation models for criminal justice reform attitudes use the factor scores generated by treating all of the attitude variables as continuous.

Table 23

Study 1 Mediation Model Fit Statistics: Immigration Attitudes

		CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
IV: Asian American ID						
Mediator: Efficacy	*full*	.805	.582	.041	1254.601 (9)***	
	stationarity	.802	.414	.050	1279.428 (18)***	24.827 (9)**
	directional[a]	.803	.453	.051	1270.705 (15)***	16.104 (6)*
Mediator: Linked fate	*full*[a]	.836	.543	.022	1090.719 (9)***	
	stationarity[a]	.833	.388	.036	1123.869 (18)***	33.150 (9)***
	directional	.833	.424	.055	1114.914 (15)***	24.195 (6)***
Mediator: Perceived discrimination	*full*[b]	.840	.530	.017	1040.741 (9)***	
	stationarity	.835	.380	.036	1080.466 (18)***	39.725 (9)***
	directional[a]	.838	.412	.038	1056.163 (15)***	15.422 (6)*
Mediator: Relative deprivation	*full*	.835	.555	.022	1140.041 (9)***	
	stationarity[c]	.833	.394	.029	1160.124 (18)***	20.083 (9)*
	directional	.834	.430	.033	1148.510 (15)***	8.469 (6)
IV: POC ID						
Mediator: Efficacy	*full*[a]	.820	.574	.037	1218.423 (9)***	
	stationarity[a]	.817	.409	.049	1247.302 (18)***	28.879 (9)***
	directional	.819	.445	.046	1229.497 (15)***	11.074 (6)†
Mediator: Linked fate	*full*	.851	.533	.015	1052.703 (9)***	
	stationarity[b]	.847	.382	.030	1089.619 (18)***	36.916 (9)***
	directional[d]	.846	.421	.048	1099.016 (15)***	46.313 (6)***

Mediator: Perceived discrimination	*full*	.855	.520	.009	1000.538 (9)***	
	stationarity[e]	.852	.371	.029	1027.963 (18)***	27.425 (9)**
	directional	.853	.405	.029	1018.217 (15)***	17.679 (6)**
Mediator: Relative deprivation	*full*	.848	.547	.017	1108.361 (9)***	
	stationarity	.847	.388	.021	1121.776 (18)***	13.415 (9)
	directional	.847	.425	.027	1120.402 (15)***	12.041 (6)†
IV: American ID						
Mediator: Efficacy	*full*[a]	.816	.589	.039	1281.846 (9)***	
	stationarity[f]	.814	.418	.047	1301.693 (18)***	19.847 (9)*
	directional[a]	.815	.457	.048	1295.348 (15)***	13.502 (6)*
Mediator: Linked fate	*full*	.844	.548	.018	1113.337 (9)***	
	stationarity	.841	.391	.031	1143.029 (18)***	29.692 (9)***
	directional[g]	.842	.428	.039	1135.324 (15)***	21.987 (6)**
Mediator: Perceived discrimination	*full*[b]	.849	.534	.012	1057.324 (9)***	
	stationarity[h]	.845	.382	.032	1090.471 (18)***	33.147 (9)***
	directional	.847	.416	.024	1071.661 (15)***	14.337 (6)*
Mediator: Relative deprivation	*full*[a]	.844	.559	.018	1157.593 (9)***	
	stationarity	.842	.397	.023	1175.482 (18)***	17.889 (9)*
	directional[a]	.842	.435	.027	1171.724 (15)***	14.131 (6)*

Note: N = 408 for all ID-immigration attitude mediation models.

Note: $\Delta\chi^2$ is vs. the full model, which has paths from all W1 variables to all W2 variables and from all W2 variables to all W3 variables and no stationarity assumption.

[a] Needed starting values for W1-W2 coefficients to converge.

[b] Needed starting values for W2-W3 coefficients to converge.
[c] Needed starting values for W2-W3 coefficients and W1 ID-RD covariance to converge.
[d] Needed starting values for W2-W3 coefficients and W1 ID-immigration attitude covariance to converge.
[e] Needed starting values for lagged and cross-lagged coefficients for both time lags and W1 ID-PD covariance to converge.
[f] Needed starting values for lagged and cross-lagged coefficients for both time lags to converge.
[g] Needed starting values for W2-W3 coefficients and W1 ID-LF covariance to converge.
[h] Needed starting values for W1-W2 coefficients and W1 ID-PD covariance to converge.

Table 24

Study 1 Mediation Model Fit Statistics: Criminal Justice Attitudes (continuous indicators)

		CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Asian American ID						
Mediator: Efficacy	*full*	.927	.301	.041	340.142 (9)***	
	stationarity	.924	.217	.049	363.390 (18)***	23.248 (9)**
	directional	.926	.235	.049	350.852 (15)***	10.710 (6)†
Mediator: Linked fate	*full*	.964	.216	.022	179.178 (9)***	
	stationarity	.960	.161	.037	207.159 (18)***	27.981 (9)***
	directional	.962	.173	.046	197.025 (15)***	17.847 (6)*
Mediator: Perceived discrimination	*full*	.973	.184	.017	133.164 (9)***	
	stationarity	.967	.144	.036	169.064 (18)***	36.100 (9)***
	directional	.971	.148	.039	148.250 (15)***	15.086 (6)*
Mediator: Relative deprivation	*full*	.958	.238	.022	216.812 (9)***	
	stationarity	.956	.173	.030	237.515 (18)***	20.703 (9)*
	directional	.958	.186	.033	225.330 (15)***	8.518 (6)

IV: POC ID						
Mediator: Efficacy	*full*	.939	.285	.037	305.756 (9)***	
	stationarity	.934	.209	.048	336.679 (18)***	30.923 (9)***
	directional	.939	.221	.042	312.095 (15)***	6.339 (6)
Mediator: Linked fate	*full*	.975	.189	.016	139.986 (9)***	
	stationarity	.970	.144	.031	170.159 (18)***	30.173 (9)***
	directional	.968	.164	.040	178.876 (15)***	38.890 (6)***
Mediator: Perceived discrimination	*full*	.983	.151	.010	92.617 (9)***	
	stationarity	.980	.116	.028	115.968 (18)***	23.351 (9)**
	directional	.982	.122	.027	106.112 (15)***	13.495 (6)*
Mediator: Relative deprivation	*full*	.967	.219	.017	184.994 (9)***	
	stationarity	.966	.157	.021	197.814 (18)***	12.820 (9)
	directional	.967	.170	.023	191.742 (15)***	6.748 (6)
IV: American ID						
Mediator: Efficacy	*full*	.929	.313	.039	368.038 (9)***	
	stationarity	.927	.226	.047	391.187 (18)***	23.149 (9)**
	directional	.930	.242	.042	372.721 (15)***	4.683 (6)
Mediator: Linked fate	*full*	.964	.229	.018	199.973 (9)***	
	stationarity	.960	.169	.033	227.578 (18)***	27.605 (9)**
	directional	.962	.180	.024	212.809 (15)***	12.836 (6)*
Mediator: Perceived discrimination	*full*	.972	.196	.012	149.146 (9)***	
	stationarity	.968	.150	.031	182.038 (18)***	32.892 (9)***
	directional	.971	.156	.026	164.137 (15)***	14.991 (6)*

Mediator: Relative deprivation	*full*	.959	.248	.018	234.020 (9)***	
	stationarity	.957	.180	.025	255.244 (18)***	21.224 (9)*
	directional	.957	.196	.026	248.414 (15)***	14.394 (6)*

Note: N = 406 for all ID-criminal justice attitude mediation models.

Note: $\Delta\chi^2$ is vs. the full model, which has paths from all W1 variables to all W2 variables and from all W2 variables to all W3 variables and no stationarity assumption.

Table 25

Study 1 Mediation Model Fit Statistics: Affirmative Action Attitudes

		CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
IV: Asian American ID						
Mediator: Efficacy	*full*	.883	.313	.045	368.663 (9)***	
	stationarity	.875	.228	.056	400.162 (18)***	31.499 (9)***
	directional	.878	.247	.055	388.744 (15)***	20.081 (6)**
Mediator: Linked fate	*full*	.942	.229	.030	202.118 (9)***	
	stationarity	.936	.170	.043	229.006 (18)***	26.888 (9)**
	directional	.938	.183	.052	219.566 (15)***	17.448 (6)**
Mediator: Perceived discrimination	*full*	.953	.200	.027	155.385 (9)***	
	stationarity	.944	.154	.041	192.981 (18)***	37.596 (9)***
	directional	.946	.166	.052	184.198 (15)***	28.813 (6)***
Mediator: Relative deprivation	*full*	.933	.253	.030	243.118 (9)***	
	stationarity	.930	.183	.039	262.994 (18)***	19.876 (9)*
	directional	.931	.200	.044	259.210 (15)***	16.092 (6)*

IV: POC ID						
Mediator: Efficacy	*full*	.904	.299	.043	337.427 (9)***	
	stationarity	.895	.221	.055	378.277 (18)***	40.850 (9)***
	directional	.899	.238	.055	361.432 (15)***	24.005 (6)***
Mediator: Linked fate	*full*	.958	.207	.026	166.992 (9)***	
	stationarity	.950	.160	.039	206.306 (18)***	39.314 (9)***
	directional	.947	.179	.055	211.658 (15)***	44.666 (6)***
Mediator: Perceived discrimination	*full*	.969	.172	.023	117.432 (9)***	
	stationarity	.961	.137	.036	154.850 (18)***	37.418 (9)***
	directional	.962	.149	.049	151.212 (15)***	33.780 (6)***
Mediator: Relative deprivation	*full*	.948	.236	.027	213.585 (9)***	
	stationarity	.944	.172	.033	236.430 (18)***	22.845 (9)**
	directional	.943	.191	.045	239.158 (15)***	25.573 (6)***
IV: American ID						
Mediator: Efficacy	*full*	.894	.322	.044	389.382 (9)***	
	stationarity	.887	.235	.054	423.555 (18)***	34.173 (9)***
	directional	.891	.254	.050	408.657 (15)***	19.275 (6)**
Mediator: Linked fate	*full*	.944	.239	.027	219.551 (9)***	
	stationarity	.940	.176	.041	244.993 (18)***	25.442 (9)**
	directional	.942	.189	.034	233.665 (15)***	14.114 (6)*
Mediator: Perceived discrimination	*full*	.956	.208	.023	167.190 (9)***	
	stationarity	.949	.158	.038	201.772 (18)***	34.582 (9)***
	directional	.950	.172	.042	197.052 (15)***	29.862 (6)***

Mediator: Relative deprivation	*full*	.939	.259	.027	255.148 (9)***	
	stationarity	.936	.187	.035	275.309 (18)***	20.161 (9)*
	directional	.934	.207	.038	278.093 (15)***	22.945 (6)***

Note: N = 408 for all ID-affirmative action attitude mediation models.

Note: $\Delta\chi^2$ is vs. the full model, which has paths from all W1 variables to all W2 variables and from all W2 variables to all W3 variables and no stationarity assumption.

Indirect effects were defined as the product (*ab*) of the W1 identity to W2 mediator path (a) and the W2 mediator to W3 attitude path (b). Total effects were defined as $ab + (x * c1) + (c1 * y)$, where *x* is the W1-W2 identity lagged path, *y* is the W2-W3 attitude lagged path, *c*1 is the direct effect of W1 identity on W2 attitude, and *c*2 is the direct effect of W2 identity on W3 attitude. The coefficients for these effects were estimated using the sem() function defaults in lavaan, and then standard errors and confidence intervals for the effects of interest were re-estimated by adding the se = “bootstrap” option.

None of the identities had significant indirect effects on immigration attitudes through any of the four hypothesized mediators. Thus, Hypotheses 14 and 16 were not supported with regard to this policy area. However, POC identity had a significant positive total effect in every model (efficacy model: t = .013, p = .001; 95% CI: [.006, .021]; linked fate model: t = .015, p = .009; 95% CI: [.004, .026]; perceived discrimination model: t = .014, p = .003; 95% CI: [.005, .023]; relative deprivation model[15]: t = .019, *p* < .001; 95% CI: [.011, .028]), and American identity had a marginally significant to significant negative total effect in every model except the efficacy model (linked fate model: t = -.009, *p* = .059; 95% CI: [-.018, -.001]; perceived discrimination model: t = -.009, *p* = .052; 95% CI: [-.018, .000]; relative deprivation model: t = -.010, *p* = .038; 95% CI: [-.019, -.001]).

Similarly, none of the identities had significant indirect effects on criminal justice attitudes through any of the four hypothesized mediators, and thus, Hypotheses 15 and 16 were not supported with regard to this issue. Surprisingly, with the mediator variables in the model, neither POC identity nor American identity had significant total effects on criminal justice attitudes. But Asian American identity had a significant, positive total effect in every model (efficacy model[16]: t = .038, *p* = .015; 95% CI: [.008, .069]; linked fate model: t = .036, *p* = .013; 95% CI: [.008, .065]; perceived discrimination model: t = .035, *p* = .018; 95% CI: [.008, .067]; relative deprivation model[17]: t = .031, *p* = .038; 95% CI: [.002, .062]).

For affirmative action, again, none of the identities had significant indirect effects through any of the four hypothesized mediators, failing to support Hypotheses 15 and 16. Although, consistent with my predictions, the coefficients for the indirect effects of POC identity through linked fate, perceived discrimination, and relative deprivation were positive, and the coefficients for the indirect effects of American identity through

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[15] Estimates are from the model with stationarity, which did not fit significantly worse than the full model.
[16] Estimates are from the directional model, which had only marginally significantly worse fit than the full model ($\chi^2_{15} = 350.852, \chi^2_9 = 340.142, \Delta\chi^2_6 = 10.710, p = .098$)
[17] Estimates are from the directional model, which did not fit significantly worse than the full model.

perceived discrimination and relative deprivation were negative, these effects were not significant. As with immigration attitudes, POC identity did have a significant, positive total effect on affirmative action attitudes in every model (efficacy model: t = .131, p = .002; 95% CI: [.046, .214]; linked fate model: t = .100, p = .023; 95% CI: [.015, .186]; perceived discrimination model: t = .106, p = .020; 95% CI: [.020, .196]; relative deprivation model: t = .125, p = .011; 95% CI: [.020, .215]). Asian American and American identities did not have significant total effects.

D. Discussion

Overall, the results of this study tended to be consistent with my hypotheses at the level of (between-person) trait covariances in the RI-CLPM. Asian Americans who identify more strongly as POC also tend to report more positive attitudes toward other racial minority groups (Hypothesis 2), and Asian Americans who identify more strongly as American tend to report more positive attitudes toward Whites (Hypothesis 1) across two different racial attitude measures (feeling thermometers and stereotype scales). Notably, however, identification as American did not share significant trait-level covariance with attitudes toward other racial minorities, contrary to Hypothesis 1, and unexpected trait covariances appeared for Asian American identity and attitudes toward nonwhites, as well as both Asian American and POC identities and attitudes toward Whites.

Consistent with my hypotheses based on the paradoxical effects literature, higher identification as American was associated, at the trait level, with less liberal immigration attitudes, less support for criminal justice reform, and less support for affirmative action (Hypothesis 13). Racial identity and POC identity tended to be positively associated with policy attitudes that favor racial minority groups, consistent with the collective action literature, in which identification with a disadvantaged group is associated with more action on behalf of the ingroup. But racial identity and POC identity did not follow the pattern of own-group and other-group policy areas that I expected: Racial identity was associated with more liberal immigration attitudes, as I expected for an own-group issue (Hypothesis 11), and it was not associated with support for criminal justice reform, as I expected for an other-group issue. But it was associated with more support for affirmative action, which I expected to be an other-group issue. POC identity was positively associated not only with the other-group issues of criminal justice reform and affirmative action (Hypothesis 12), but also immigration. Nonetheless, the pattern of positive trait covariances with racial and POC identity and negative trait covariances with American identity is generally consistent with the collective action and paradoxical effects literatures, respectively.

However, Study 1 provides only inconsistent evidence that identification with their racial group or either common ingroup *precedes* changes in Asian Americans' racial attitudes or attitudes toward polices associated with racial minority groups. In the CLPM, which reflect a combination of between-person and within-person dynamics, Asian Americans who identify more strongly as POC appear to show improvements in their stereotype ratings of Black and Hispanic Americans, though not in their feeling thermometer ratings of the same groups, compared to Asian Americans who identify less strongly as POC. Asian Americans who identify more strongly as American tend to show improvements in their attitudes toward White Americans (on both measures) compared to those who identify less strongly as American. The RI-CLPM with stationarity suggests that increases in POC identification might specifically predict improvements in Black and Hispanic stereotype ratings at the within-person level. But the cross-lagged effects of American identity on attitudes toward Whites that appeared in the CLPM are not present at the within-person level; in fact, the RI-CLPM with stationarity suggests that increased identification as American at the within-person level predicts worsening ratings of Whites on the stereotype scale, and vice versa. By contrast, increased identification as American seems to predict improvements in feeling thermometer ratings of other minorities at the within-person level, consistent with Hypothesis 1, though that portion of the hypothesis is not supported at the between-person level or with regard to the stereotype scales.

Despite the trait-level covariances, cross-lagged effects were generally not significant for attitudes toward immigration and criminal justice reform. This could be due to the particularly high stability of those attitudes among respondents in this study, which could have limited the variance left for other variables to explain. The only significant cross-lagged effect for either of these policy areas in the CLPM was a small, positive effect of POC identity on immigration attitudes (which I did not expect for an own-group issue), and the only significant (within-person) cross-lagged effect in the RI-CLPM was a negative effect of POC identity on one version of the criminal justice attitude variable (the opposite of what I expected). Thus, Hypotheses 11-13 were not supported for these issues.

With regard to affirmative action, POC identity had significant cross-lagged effects in both the CLPM and RI-CLPM, supporting Hypothesis 12 at both the between-person and within-person levels. However, contrary to Hypothesis 13 and the negative trait covariance between the two variables, increases in American identity at the within-person level appear to predict increases in support for affirmative action and vice versa. This effect, together with its within-person cross-lagged effects on White stereotype and nonwhite FT ratings, suggests that identification as American, in particular, could have different effects at the between-person and within-person levels and that one should be careful when extrapolating from CLPM results (as well as cross-sectional correlational results) to theories about what effects within-person changes in group identification can have.

The distinction between between-person and within-person effects is practically, as well as theoretically, important in the context of prejudice reduction because significant within-person cross-lagged effects in models like the RI-CLPM provide insight into whether an intervention to shift individuals' group identification could potentially change those individuals' attitudes. In this study, increases in POC identity were associated with improvements in one measure of attitudes toward other racial minorities and with increased support for affirmative action at both the between-person and within-person levels. Together with the low levels of POC identification among the respondents in this study and the pilot study, which suggest the potential for particularly large increases in identification with that common ingroup, the within-person effects suggest that increasing Asian Americans' identification as POC could be a pathway for interventions to increase their solidarity with other racial minority groups. (However, negative cross-lagged effects in the RI-CLPM for one version of the criminal justice attitudes variable cautions against moving toward interventions without further research.) The inconsistent and sometimes unexpected effects of American identity, on the other hand, make it a less attractive target for potential interventions, at least with Asian Americans.

A major limitation of this study was the stability of most of the key variables across the study's time span. I expected some stability in the identity and racial attitude variables, as those have been treated as stable, endogenous, individual difference variables in much of the political psychology literature, and the potential for trait-like stability was why the use of RI-CLPM in this study is an important contribution to the literature on identity and racial attitudes. However, the stability of the policy attitudes in this study, especially the extremely high stability of the immigration and criminal justice attitudes, was unexpected given the extensive literature on political non-attitudes among the general public (e.g., Converse, 1964; Zaller, 1992). Although there is evidence that policy attitudes associated with race (especially affirmative action-related attitudes) are more stable than economic policy attitudes (e.g., Zaller, 1992, ch. 4), they are not the kind of culture war issues (e.g., abortion or same-sex marriage) that, for example, have been shown to shift political affiliation (Goren & Chapp, 2017). The three-item scales in this study could have had some aggregation effects on measured stability (Ansolabhere et al., 2008), but the stable policy attitude scales Ansolabhere et al. (2008) examined tended to combine many more items across broader policy areas. On the other hand, using factor scores to aggregate items could account for some of the unexpectedly high stability, not only in policy attitudes but also in group identification and racial attitudes.[18]

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[18] For comparison, correlations across waves were calculated for composite scores (i.e., the average across scale items in each wave) of the Huddy scale for each identity, the nonwhite FTs and stereotypes, and the immigration and criminal justice policy attitudes. Although the composite scores also appeared to be highly stable, they were less stable

Furthermore, participant and contextual factors could explain why policy attitudes were so stable in this study. Respondents in both Study 1 and the pilot study tended to have high incomes and high educational attainment, and results from the political knowledge battery in the pilot study suggest that Asian Americans on Prolific might be especially politically sophisticated. Thus, this study might reflect the attitudes of an Asian American political elite rather than Asian Americans in the general public. Additionally, the data were collected at the end of 2020, after four years of inflammatory rhetoric on immigration and in the wake of the police killing of George Floyd and the protests that followed; thus, immigration and criminal justice reform might have been more salient than they ordinarily would be, which could have resulted in stronger and more accessible attitudes that would have produced more stable responses to those policy items. Alternatively, policy attitudes, as well as identity and racial attitudes, might simply be stable among adults across a 1- to 2-month time span. Future research could follow respondents over years instead of months or focus on younger adults, perhaps college students in particular, for whom aspects of identity such as centrality and commitment can still change (e.g., Ramos et al., 2012; Fuller-Rowell et al., 2013) and racial and political attitudes might also still have room to change. On the other hand, to better inform the development of interventions, future studies could manipulate different aspects of identity (such as identity salience) to examine whether similar identity-attitude

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than their factor score counterparts, as one might expect because factor scores (at least in theory) capture latent constructs without measurement error, and measurement error is still present in composite scores.

dynamics apply when a change in identity comes from an intervention as exist over the long term.

Overall, while POC identity generally related to racial and policy attitudes in this study as expected (predicting more positive attitudes toward other racial minorities and toward policies associated with other racial minority groups), American identity produced an inconsistent pattern of results. Thus, Study 1 suggests that 1) POC identity fits into the common ingroup identity model as a superordinate identity that is associated with less prejudice against other superordinate group members, but 2) POC identity is associated with, if anything, more support for policies that benefit minority groups, in contrast to broader superordinate identities in the paradoxical effects literature but consistent with the collective action and group consciousness literatures. (Racial identity also appears to be associated with more support for policies that benefit minority groups, consistent with the collective action and group consciousness literatures, though this applied not only to the own-group issue of immigration but also to the other-group issue of affirmative action.) Study 1 provides some evidence of American identity being associated with both less prejudice and less support for policies that benefit minority groups, but it also provides some contrary evidence. However, much of the evidence from this study that is consistent with the existing literature is at the trait level (and therefore not directional), and thus, further research is necessary to test the causal implications of these theories for Asian Americans' racial, POC, and American identities.

Additionally, further research should explore the extent to which the dynamics of racial, POC, and American identities and racial and political attitudes are similar or different across racial minority groups. Study 2 begins to address this last question.

Chapter 4: Study 2

Study 2 examines the effects of POC and American identities for two other racial minority groups: African Americans and Latinos. This study uses data from the University of Minnesota Center for the Study of Political Psychology's (CSPP) 2020 Presidential Election Panel Study, a 3-wave longitudinal study with data collection in October before the 2020 elections (Waves 1 and 2) and in November after the elections (Wave 3). The CSPP study was a multi-investigator study, and Study 2 was one of several modules included in the study. The data from this study allowed me to examine whether racial, POC, and American identities have similar or different patterns of results on the racial and political attitudes of members of different racial minority groups.

A. Method

Respondents

Respondents were adult United States citizens recruited through YouGov. They consist of a nationally representative sample, plus an oversample of African Americans. The sample included 658 respondents who self-identified as Black (38% male) and 272 respondents who self-identified as Hispanic or Latino (57% male). Both the Black and Latino respondents in this study tended to be older than the Asian American respondents in Study 1 (Black respondents: range = 18-85, Mean = 48.8, SD = 16.2; Latino respondents: range = 18-83, Mean = 42.3, SD = 16.7). The median income for Black respondents was $30,000-39,999, and the median income for Latino respondents was $40,000-49,999. For both groups, the modal response for education level was "high school graduate"; 19% of Black respondents and 16% of Latino respondents had a 4-year college degree or higher (compared to 60% of the Asian American respondents in Study

1). Like the Asian American respondents in Study 1, despite being thought of as a largely immigrant group, most of the Latino respondents in this study were born in the U.S. (18% immigrant citizens, 35% first-generation citizens, 24% second-generation citizens, 24% third-generation and above). The vast majority of Black respondents were born in the U.S. (9% immigrant citizens, 8% first-generation citizens, 4% second-generation citizens, 80% third-generation and above).

Both groups showed a trimodal distribution on political ideology, though more identified as at least slightly liberal (42% of Black respondents; 39% of Latino respondents) than identified as at least slightly conservative (17% of Black respondents; 26% of Latino respondents). A large majority of Black respondents (72%) and a slight majority of Latino respondents (51%) identified as Democrats or Democratic leaning. Most reported being registered to vote in the 2016 elections (88% of Black respondents; 86% of Latino respondents).

The study was administered in 3 waves: Wave 1 ran from October 6 to October 14, 2020, Wave 2 ran from October 25 to November 3, 2020,[1] and Wave 3 ran from November 9 to November 16, 2020. Of the 658 Black respondents who completed Wave 1, 531 completed Wave 2 (19% attrition), and 441 completed Wave 3 (17% attrition from Wave 2; 33% attrition overall). Of the 272 Latino respondents who completed Wave 1, 146 completed Wave 2 (46% attrition), and 120 completed Wave 3 (18% attrition from Wave 2; 56% attrition overall). Respondents who completed more waves tended to be

[1] Election Day was November 3. Despite a small number of Wave 2 responses collected on that day, we treat Wave 2 as pre-election, largely because the results of the Presidential election were not officially announced until November 7.

older, and respondents in the lowest income category and respondents who did not vote in 2016 appeared to be more likely to drop out between waves. Among Latino respondents, men and those with less education dropped out in higher numbers after the first wave than women and those with more education. There were trends for Black conservatives to drop out at slightly higher rates than Black moderates and liberals and for Latino extreme liberals and Democrats to complete all three waves of the study at higher rates than Latino respondents in other ideological or party identity categories. Among Black respondents, those who were not registered to vote appeared to be more likely to drop out after the first wave.

Materials and Procedure

An abbreviated version of the Study 1 materials was included in the CSPP 2020 study. Racial, POC, and American identities were measured using 2-item versions of the Huddy et al. (2015) identity scale, specifically the items "how important is being __ to you?" and "to what extent do you think of yourself as being __?" Responses were on a 5-point scale, with "moderately important" added between "slightly important" and "very important" for the first item and "quite a bit" added between "somewhat" and "a great deal" for the second item. These two items generally formed a reliable measure, for both Black and Latino respondents, of racial identity (Black respondents: Wave 1 α = .87, Wave 2 α = .83, Wave 3 α = .87; Latino respondents: Wave 1 α = .87, Wave 2 α = .91, Wave 3 α = .89), POC identity (Black respondents: α = .87, .85, .85; Latino respondents: α = .85, .78, .84), and American identity (Black respondents: α = .87, .88, .88; Latino respondents: α = .89, .87, .90). Accordingly, responses to the two scale items were averaged to form a composite score for each identity in each wave.

Racial attitude items consisted of feeling thermometers (FT) for Whites, Blacks, Latinos, and Asians. FT ratings of Latinos and Asians were averaged in each wave for Black respondents (Wave 1 α = .91; Wave 2 α = .89; Wave 3 α =.89), and FT ratings of Blacks and Asians were averaged in each wave for Latino respondents (α = .85 all 3 waves) to form composite scores of attitudes toward other racial minority groups.

Support for change consisted of 2 items measuring attitudes toward immigration policy—one asking respondents' opinion on the number of immigrants who should be allowed to enter the U.S. (1 = increased a lot; 7 = decreased a lot) and one asking how much they support or oppose ending criminal penalties for people crossing the border illegally (1 = strongly oppose; 7 = strongly support)—as well as items measuring attitudes toward Black Lives Matter (1 = very positive; 5 = very negative), mandatory minimum sentencing (1 = "Mandatory minimum sentences should be given in all cases where they apply, with no exceptions." 2 = "Even where a mandatory minimum sentence applies, a judge should have the freedom to give a shorter sentence if the judge finds compelling circumstances."), and support for the protests after George Floyd's death (1 = strongly support; 7 = strongly oppose). Because responses to the immigration items did not show adequate internal consistency (Black respondents: α = .12, .22, .08; Latino respondents: α = .28, .52, .46), these items were treated as separate measures of immigration policy attitudes in further analyses. The Black Lives Matter and George Floyd protests items did show some amount of internal consistency (Black respondents: α = .75, .79, .82; Latino respondents: α = .91, .89, .96), and thus, responses to those two items were averaged (after 0-1 coding) to form a composite score for each respondent in each wave. However, the mandatory minimum sentence item was only weakly correlated with the other two items and was treated as a separate measure of criminal justice reform attitudes in further analyses.

Of the potential mediators, this study only included the linked fate items. However, if Sanchez and Vargas's (2016) findings still hold, linked fate should adequately represent the single-factor group consciousness construct for Black respondents, at least with regard to their racial identity. For Latino respondents, linked fate might still be a partial mediator even if it does not capture the full scope of group consciousness.

Respondents were asked their race and gender, as well as their political ideology, political party affiliation (which was recoded onto a 7-point scale as in Study 1), and whether they were registered to vote as part of the study. Additionally, YouGov provided respondents' birth year, education, family income, and immigration background. Based on these variables, I created dummy variables for gender (1 = male; 0 otherwise) and immigrant status (1 = immigrant; 0 otherwise), and I subtracted respondents' birth years from 2020 to create a variable for age.

Toward the beginning of Wave 1, respondents were asked to select one or more racial or ethnic categories that describe them. The racial category or categories they selected were then piped into the racial identity and linked fate questions, so that, for example, a respondent who chose Black would be asked, "how important is being a Black person to you?" Respondents who selected more than one racial category were asked the racial identity and linked fate questions for each racial category they selected. All respondents were asked the racial identity, American identity, and racial linked fate questions, but only respondents who selected at least one racial category other than White were asked the POC identity and linked fate questions.

In Wave 1, respondents were first asked their gender, employment status, and race, followed by questions about their political orientation and interest in politics. Next, they were presented with feeling thermometers for a variety of people and groups, including the racial groups relevant to this study. Following these were a set of policy attitude items, including the immigration and criminal justice reform items relevant to this study. Then, after a number of items unrelated to this study, respondents were asked the racial and POC linked fate questions and after another set of items unrelated to this study, they were given the 2-item identity scale for a number of identities including American, POC, and racial identities. Waves 2 and 3 followed a similar order but did not ask the demographic and political orientation questions from Wave 1 except that Wave 3 included a question about respondents' political party affiliation.

All items were recoded to range from 0 to 1. Items that were averaged to form composite scores were 0-1 coded before averaging. Composite scores were used for racial, POC, and American identities (average of 2 items per time point for each identity); nonwhite FTs (average of Latino and Asian FTs at each time point for Black respondents; average of Black and Asian FTs at each time point for Latino respondents); and criminal justice reform attitudes (average of BLM and protest items at each time point; mandatory minimum sentence item was analyzed separately). I included age, the gender dummy variable, education, family income, the immigrant status dummy variable, political ideology, and party affiliation as covariates in panel models.

As in Study 1, cross-lagged panel models and random-intercepts cross-lagged panel models were analyzed through structural equation modeling using the lavaan package in R. Data from Black and Latino respondents were analyzed separately. As in Study 1, for each identity-attitude pair, I tested CLPM with and without demographic and political covariates and with and without stationarity across lags, and I tested RI-CLPM with and without stationarity. Because Study 2 did not involve factor scores or extensive model convergence problems, panel models were fit using full-information maximum likelihood estimation or WLSMV estimation with pairwise deletion.

B. Results

1. Descriptive Statistics

Means and standard deviations for the identity, racial attitude, policy attitude, and linked fate variables are presented in Table 26.

Table 26

Study 2 Variable Means and Standard Deviations

	Wave 1		**Wave 2**		**Wave 3**	
	n	*Mean (SD)*	*n*	*Mean (SD)*	*n*	*Mean (SD)*
Racial ID[a]						
Black	658	4.29 (1.09)	531	4.26 (1.05)	441	4.32 (1.05)
Latino	272	3.77 (1.20)	146	3.91 (1.14)	120	3.91 (1.20)
POC ID						
Black	658	4.26 (1.10)	531	4.22 (1.09)	441	4.28 (1.09)
Latino	272	2.88 (1.38)	146	3.09 (1.25)	120	3.08 (1.38)
American ID						
Black	658	3.79 (1.21)	531	3.89 (1.13)	441	3.85 (1.15)
Latino	272	3.82 (1.15)	146	3.87 (1.06)	120	3.89 (1.13)
Nonwhite FT comp						
Black	658	67.5 (25.4)	531	69.1 (24.5)	441	67.3 (25.6)
Latino	272	69.4 (24.7)	146	70.8 (24.9)	120	70.3 (23.8)
White FT						

Black	658	60.4 (27.4)	531	61.7 (27.9)	441	61.6 (27.7)
Latino	272	62.7 (27.0)	146	66.5 (25.6)	120	64.4 (25.4)
Immigration: # immigrants[b]						
Black	658	4.39 (1.52)	531	4.30 (1.53)	441	4.33 (1.50)
Latino	272	4.45 (1.61)	146	4.26 (1.65)	120	4.45 (1.62)
Immigration: Ending criminal penalties						
Black	658	3.93 (1.77)	531	3.87 (1.85)	441	3.93 (1.83)
Latino	272	4.26 (1.90)	146	4.26 (1.98)	120	4.07 (2.12)
Criminal justice: BLM/protests[c]						
Black	658	.773 (.249)	531	.772 (.258)	441	.775 (.259)
Latino	272	.572 (.348)	146	.563 (.333)	120	.572 (.368)
Criminal justice: Mandatory minimum sentence[d]						
Black	658	.728 (.445)	531	.753 (.431)	441	.776 (.418)
Latino	272	.658 (.475)	146	.712 (.454)	120	.733 (.444)
Linked fate: race[e]						
Black	556	2.74 (1.16)	422	2.80 (1.18)	386	2.80 (1.21)
Latino	212	2.18 (1.14)	118	2.32 (1.14)	101	2.35 (1.16)
Linked fate: POC						
Black	540	2.55 (1.20)	410	2.57 (1.19)	372	2.70 (1.17)
Latino	221	2.12 (1.14)	118	2.20 (1.17)	102	2.21 (1.15)

[a] Identity composite variables are on a 5-point scale, with higher scores indicating greater identification with the group.
[b] Both immigration items are on a 7-point scale. The number of immigrants item was recoded so higher scores on both items indicate more liberal immigration attitudes.
[c] BLM/protest composite scores are reported on a 0-1 scale, with higher scores indicating more support.
[d] Means on the mandatory minimum sentence item reflect the proportion of respondents who chose the answer favoring judges' ability to give sentences shorter than the mandatory minimum.
[e] Linked fate is on a 4-point scale (1 = no linked fate; 2 = not very much; 3 = some; 4 = a lot).

Racial identification and American identification tended to be high among both Black and Latino respondents across waves, but Latino respondents' identification as

POC was close to the scale midpoint and, in Wave 1, was slightly below the midpoint.

For Black respondents, racial identity and POC identity were highly correlated at each time point (r = .83-.88); this correlation was somewhat lower for Latino respondents (r = .52-.66), though for both groups it was higher than the correlation between either of these identities and American identity. (See Table 27.)

Table 27

Study 2 Identity Intercorrelations

	Racial identity	POC identity	American identity
Black respondents W1			
Racial identity	1.000		
POC identity	.875	1.000	
American identity	.308	.362	1.000
Black respondents W2			
Racial identity	1.000		
POC identity	.865	1.000	
American identity	.319	.344	1.000
Black respondents W3			
Racial identity	1.000		
POC identity	.829	1.000	
American identity	.290	.327	1.000
Latino respondents W1			
Racial identity	1.000		
POC identity	.520	1.000	
American identity	.259	.032	1.000
Latino respondents W2			
Racial identity	1.000		
POC identity	.627	1.000	
American identity	.281	.105	1.000
Latino respondents W3			
Racial identity	1.000		
POC identity	.664	1.000	
American identity	.236	.004	1.000

Both Black and Latino respondents tended to rate other racial minority groups above the midpoint on the feeling thermometers (Black respondents: Wave 1 Mean = 67.5, SD = 25.4; Wave 2 Mean = 69.1, SD = 24.5; Wave 3 Mean = 67.3, SD = 25.6; Latino respondents: Wave 1 Mean = 69.4, SD = 24.7, Wave 2 Mean = 70.8, SD = 24.9, Wave 3 Mean = 70.3, SD = 23.8). Both groups also tended to rate Whites above the midpoint, though the average White FT ratings were somewhat lower than the average nonwhite FT ratings (Black respondents: Wave 1 Mean = 60.4, SD = 27.4; Wave 2 Mean = 61.7, SD = 27.9; Wave 3 Mean = 61.6, SD = 27.7; Latino respondents: Wave 1 Mean = 62.7, SD = 27.0; Wave 2 Mean = 66.5, SD = 25.6; Wave 3 Mean = 64.4, SD = 25.4).

Although the mean responses for both groups on the number of immigrants item were above the midpoint (Black respondents: Mean = 4.30-4.39 on a 7-point scale; Latino respondents: Mean = 4.26-4.45), Black respondents were on average just below the midpoint in support for ending criminal penalties for immigration (Mean = 3.87-3.93 on a 7-point scale), and Latino respondents were slightly to somewhat above the midpoint (Mean = 4.07-4.26). Both groups appeared to support criminal justice reform, but Black respondents tended to show more support than Latino respondents (BLM/protests, Black respondents: Mean = .772-.775 on a 0-1 scale, Latino respondents: Mean = .563-.572; mandatory minimum sentence, Black respondents: Mean = .728-.776, Latino respondents: Mean = .658-.733).

Stability of measures. Correlations of each variable with itself across waves are presented in Table 28. As in Study 1, the identity variables (*r* = .73-.88) and nonwhite FT composite scores (*r* = .73-.83) show high levels of stability. And the criminal justice attitude composite formed from the BLM and protest items was even more stable, especially among Latino respondents (Black respondents: r = .86-.90; Latino respondents: r = .93-.97). The number of immigrants item was also fairly stable (r = .67-.84), though less so than immigration attitudes appeared to be in Study 1. However, in contrast to Study 1, one of the immigration items in Study 2 did not appear to be highly stable across waves (r = .27-.40), and one of the criminal justice items (the mandatory minimum sentence item) showed an intermediate but highly variable level of stability (r = .38-.57).

Table 28

Study 2 Variable Autocorrelations

	Black respondents			**Latino respondents**		
	W1-W2	*W2-W3*	*W1-W3*	*W1-W2*	*W2-W3*	*W1-W3*
Identity composite scores						
Racial ID	.768	.785	.773	.826	.832	.759
POC ID	.766	.796	.742	.736	.731	.793
American ID	.792	.826	.818	.828	.885	.870
Racial attitude variables						
Non-White FT composite score	.790	.792	.758	.731	.822	.827
White FT	.686	.735	.707	.684	.755	.644
Policy attitude variables						
Immigration: number of immigrants	.670	.689	.694	.670	.837	.815
Immigration: ending criminal penalties	.270	.299	.313	.360	.399	.343
Criminal justice: BLM/protests composite	.862	.897	.861	.927	.967	.970
Criminal justice: mandatory minimum sentence	.378	.511	.448	.465	.566	.408
Linked fate						
Race	.722	.730	.701	.589	.637	.590
POC	.612	.674	.626	.545	.653	.526
Composite score	.706	.733	.677	.598	.651	.580

2. Identity and Racial Attitudes

Again, I hypothesized that identification as POC would predict more positive attitudes toward other racial minority groups (Hypothesis 2), and identification as American would predict more positive attitudes toward both other racial minority groups and Whites (Hypothesis 1).

a. Cross-lagged panel models. Fit statistics for the identity-nonwhite FT panel models are provided in Tables 29 (Black respondents) and 30 (Latino respondents). SRMR for all CLPM models met the Hu and Bentler (1999) criteria. CFI was close to the criterion in all of the models for Black respondents (CFI > .92) and met the criterion in the models for Black respondents' POC identity and nonwhite FTs with covariates. But it was in this range for Latino respondents only for the model with racial identity and was lower in the models with POC (CFI = .849-.898) and American (CFI = .875-.924) identities. RMSEA indicated poor fit for all CLPM models (RMSEA ≥ .143).

Table 29

Study 2 Panel Model Fit Statistics: Non-White FTs, Black Respondents

	CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
Racial ID					
CLPM no covariates	.930	.231	.040	144.394 (4)***	
CLPM no cov w/ stationarity	.928	.165	.047	151.719 (8)***	7.325 (4)
CLPM w/ covariates	.943	.227	.020	140.085 (4)***	
CLPM w/ cov w/ stationarity	.942	.162	.023	146.547 (8)***	6.462 (4)
RI-CLPM	1.000	.030	.010	1.576 (1)	142.818 (3)***
RI-CLPM w/ stationarity	1.000	.000	.015	4.234 (5)	2.658 (4)

POC ID					
CLPM no covariates	.947	.201	.035	110.739 (4)***	
CLPM no cov w/ stationarity	.943	.147	.042	122.035 (8)***	11.296 (4)*
CLPM w/ covariates	.955	.201	.018	110.861 (4)***	
CLPM w/ cov w/ stationarity	.953	.146	.021	120.373 (8)***	9.512 (4)*
RI-CLPM	.999	.046	.011	2.399 (1)	108.340 (3)***
RI-CLPM w/ stationarity	.997	.042	.023	10.708 (5)†	8.309 (4)†
American ID					
CLPM no covariates	.930	.241	.039	156.572 (4)***	
CLPM no cov w/ stationarity	.926	.175	.050	169.483 (8)***	12.911 (4)*
CLPM w/ covariates	.946	.229	.018	142.475 (4)***	
CLPM w/ cov w/ stationarity	.945	.164	.022	149.719 (8)***	7.244 (4)
RI-CLPM	.997	.101	.021	7.740 (1)**	148.832 (3)***
RI-CLPM w/ stationarity	.998	.035	.022	9.115 (5)	1.375 (4)

Note: N = 658 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 30

Study 2 Panel Model Fit Statistics: Non-White FTs, Latino Respondents

	CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
Racial ID					
CLPM no covariates	.926	.203	.044	48.932 (4)***	
CLPM no cov w/ stationarity	.927	.143	.050	52.460 (8)***	3.528 (4)
CLPM w/ covariates	.945	.200	.023	47.623 (4)***	
CLPM w/ cov w/ stationarity	.944	.143	.026	52.448 (8)***	4.825 (4)

RI-CLPM	1.000	.030	.015	1.252 (1)	47.680 (3)***
RI-CLPM w/ stationarity	.995	.047	.034	7.957 (5)	6.705 (4)
POC ID					
CLPM no covariates	.854	.272	.063	84.382 (4)***	
CLPM no cov w/ stationarity	.849	.195	.076	90.641 (8)***	6.259 (4)
CLPM w/ covariates	.898	.267	.032	81.765 (4)***	
CLPM w/ cov w/ stationarity	.893	.194	.039	89.620 (8)***	7.855 (4)†
RI-CLPM	1.000	.000	.009	0.412 (1)	83.970 (3)***
RI-CLPM w/ stationarity	.993	.052	.042	8.617 (5)	8.205 (4)†
American ID					
CLPM no covariates	.896	.254	.050	74.348 (4)***	
CLPM no cov w/ stationarity	.875	.197	.076	92.128 (8)***	17.780 (4)**
CLPM w/ covariates	.924	.255	.027	74.964 (4)***	
CLPM w/ cov w/ stationarity	.906	.201	.037	95.622 (8)***	20.658 (4)***
RI-CLPM	1.000	.000	.004	0.110 (1)	74.238 (3)***
RI-CLPM w/ stationarity	.993	.061	.045	10.015 (5)†	9.905 (4)*

Note: N = 272 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Fit statistics for the identity-White FT panel models are provided in Tables 31 (Black respondents) and 32 (Latino respondents). Again, SRMR indicated good fit (SRMR ≤ .071). CFI met the fit criterion for the model of Latino respondents' racial identity and White FT ratings (CFI = .973-.982) and was close to the criterion in all of the other models (CFI = .910-.956) except the one for Latino respondents' POC identity (CFI = .881-.927). RMSEA again indicated poor fit for all CLPM models, though the models for Latino respondents' racial identity with stationarity were close to the fit criterion (RMSEA = .081 without covariates; .077 with covariates).

Table 31

Study 2 Panel Model Fit Statistics: White FT, Black Respondents

	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
Racial ID					
CLPM no covariates	.910	.243	.049	160.023 (4)***	
CLPM no cov w/ stationarity	.910	.171	.051	162.826 (8)***	2.803 (4)
CLPM w/ covariates	.928	.240	.025	155.486 (4)***	
CLPM w/ cov w/ stationarity	.929	.169	.026	159.025 (8)***	3.539 (4)
RI-CLPM	.999	.055	.013	2.958 (1)†	157.065 (3)***
RI-CLPM w/ stationarity	1.000	.000	.018	4.828 (5)	1.870 (4)
POC ID					
CLPM no covariates	.928	.217	.045	128.456 (4)***	
CLPM no cov w/ stationarity	.929	.152	.046	130.135 (8)***	1.679 (4)
CLPM w/ covariates	.941	.217	.023	127.746 (4)***	
CLPM w/ cov w/ stationarity	.942	.152	.024	130.038 (8)***	2.292 (4)
RI-CLPM	.998	.079	.016	5.110 (1)*	123.346 (3)***
RI-CLPM w/ stationarity	.998	.034	.022	8.861 (5)	3.751 (4)
American ID					
CLPM no covariates	.918	.247	.047	164.981 (4)***	
CLPM no cov w/ stationarity	.916	.177	.051	172.008 (8)***	7.027 (4)
CLPM w/ covariates	.936	.239	.023	154.244 (4)***	
CLPM w/ cov w/ stationarity	.936	.168	.024	157.196 (8)***	2.952 (4)
RI-CLPM	.999	.052	.013	2.750 (1)†	162.231 (3)***

RI-CLPM w/ stationarity	.999	.029	.021	7.677 (5)	4.927 (4)

Note: N = 658 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 32

Study 2 Panel Model Fit Statistics: White FT, Latino Respondents

	CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
Racial ID					
CLPM no covariates	.973	.114	.032	18.263 (4)**	
CLPM no cov w/ stationarity	.973	.081	.044	22.194 (8)**	3.931 (4)
CLPM w/ covariates	.982	.108	.015	16.657 (4)**	
CLPM w/ cov w/ stationarity	.982	.077	.020	20.826 (8)**	4.169 (4)
RI-CLPM	1.000	.000	.004	0.060 (1)	18.203 (3)***
RI-CLPM w/ stationarity	1.000	.000	.025	3.858 (5)	3.798 (4)
POC ID					
CLPM no covariates	.883	.218	.056	55.533 (4)***	
CLPM no cov w/ stationarity	.881	.156	.070	60.618 (8)***	5.085 (4)
CLPM w/ covariates	.927	.212	.028	52.839 (4)***	
CLPM w/ cov w/ stationarity	.926	.151	.035	57.704 (8)***	4.865 (4)
RI-CLPM	1.000	.000	.003	0.045 (1)	55.488 (3)***
RI-CLPM w/ stationarity	1.000	.000	.024	2.221 (5)	2.176 (4)
American ID					
CLPM no covariates	.938	.187	.041	42.039 (4)***	
CLPM no cov w/ stationarity	.913	.157	.071	61.403 (8)***	19.364 (4)***
CLPM w/ covariates	.956	.187	.020	42.159 (4)***	
CLPM w/ cov w/ stationarity	.934	.161	.033	64.726 (8)***	22.567 (4)***

RI-CLPM	1.000	.000	.008	0.309 (1)	41.730 (3)***
RI-CLPM w/ stationarity	.994	.052	.040	8.657 (5)	8.348 (4)†

Note: N = 272 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Stationarity constraints significantly reduced model fit for Black respondents' POC identity and nonwhite FTs (without covariates: $\chi^2_4 = 110.739, \chi^2_8 = 122.035, \Delta\chi^2_4 = 11.296, p = .023$; with covariates: $\chi^2_4 = 110.861, \chi^2_8 = 120.373, \Delta\chi^2_4 = 9.512, p = .050$) and American identity and nonwhite FTs without covariates ($\chi^2_4 = 156.572, \chi^2_8 = 169.483, \Delta\chi^2_4 = 12.911, p = .012$) and for Latino respondents' American identity and nonwhite FTs (without covariates: $\chi^2_4 = 74.348, \chi^2_8 = 92.128, \Delta\chi^2_4 = 17.780, p = .001$; with covariates: $\chi^2_4 = 74.964, \chi^2_8 = 95.622, \Delta\chi^2_4 = 20.658, p < .001$). Additionally, stationarity constraints marginally reduced fit for Latino respondents' POC identity and nonwhite FTs with covariates ($\chi^2_4 = 81.765, \chi^2_8 = 89.620, \Delta\chi^2_4 = 7.855, p = .097$). Stationarity constraints also significantly reduced model fit for Latino respondents' American identity and White FTs (without covariates: $\chi^2_4 = 42.039, \chi^2_8 = 61.403, \Delta\chi^2_4 = 19.364, p < .001$; with covariates: $\chi^2_4 = 42.159, \chi^2_8 = 64.726, \Delta\chi^2_4 = 22.567, p < .001$). Thus, results for Black respondents' POC and American identities and nonwhite FTs and Latino respondents' American identity and all FTs are reported below based on the models without stationarity.

For Black respondents, both POC identity and American identity in Wave 2 had significant, positive cross-lagged effects on nonwhite FT ratings in Wave 3 (POC identity: *b* = .080, *SE* = .028, *p* = .005; American identity: *b* = .096, *SE* = .026, *p* < .001).

However, FT ratings in Wave 1 also had a significant positive effect on POC identity in Wave 2 (b = .089, SE = .030, p = .004). Additionally, racial identity had a significant positive cross-lagged effect on nonwhite FT ratings even though it was not predicted to be related to racial attitudes (ID-attitude: b = .051, SE = .019, p = .008). (Figure 27 presents CLPM results for all 3 identities—without stationarity for POC and American identities and with stationarity for racial identity.) Thus, there is evidence for Hypotheses 1 and 2 among Black respondents, but it is inconsistent across time lags, there is evidence of a reverse effect from nonwhite FT ratings to POC identity, and racial identity unexpectedly shows a similar effect.

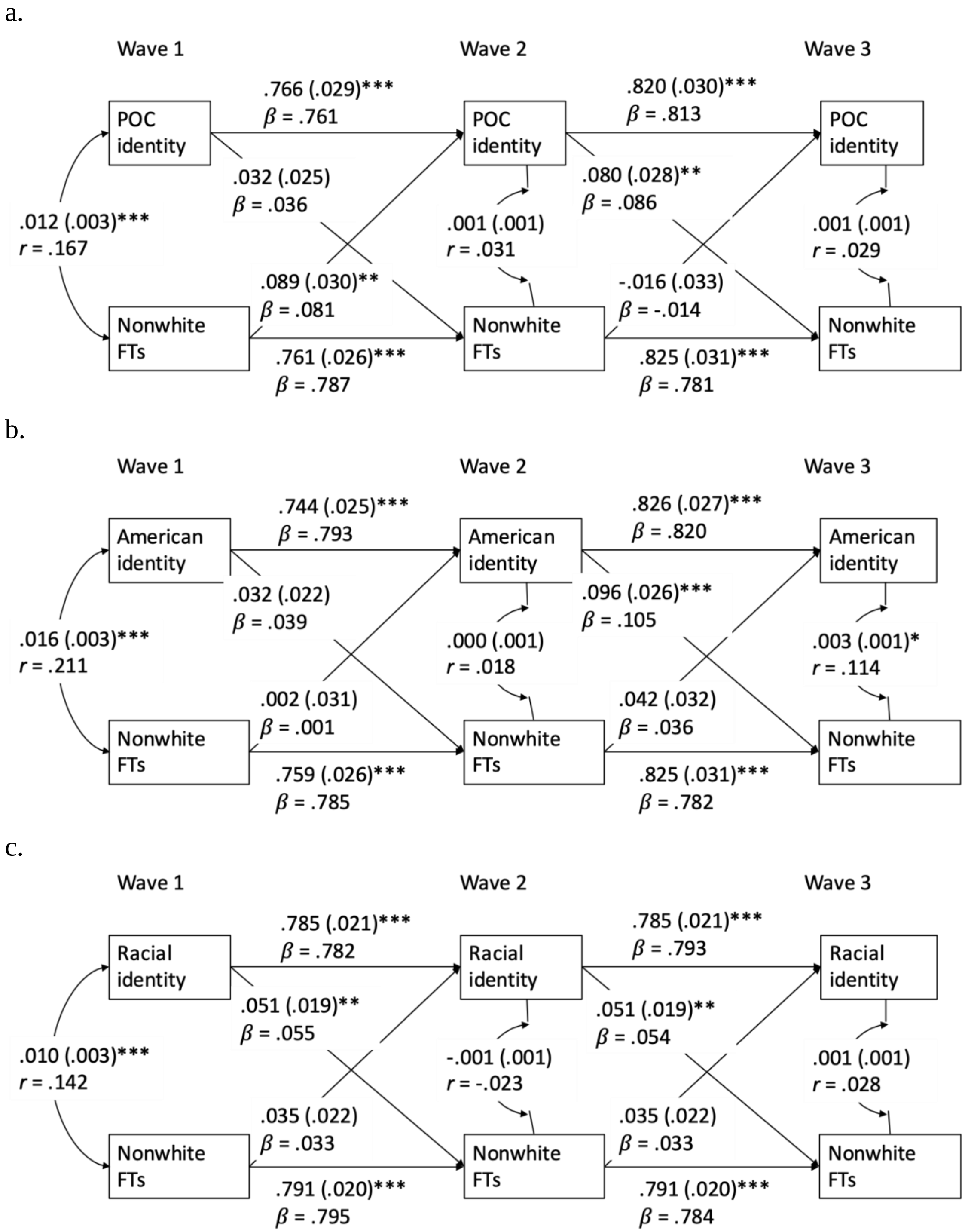


Figure 27. Study 2 CLPM for Black respondents' POC identity and nonwhite FTs, with no stationarity constraints (a); American identity and nonwhite FTs, with no stationarity constraints (b); and racial identity and nonwhite FTs, with stationarity constraints on

lagged and cross-lagged coefficients (c). These models do not include covariates. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

For Latino respondents, American identity in Wave 1 had a significant positive effect on nonwhite FT ratings in Wave 2 ($b = .158$, $SE = .051$, $p = .002$) (Figure 28). There is some evidence of a similar effect of POC identity, but only in the model with covariates ($b = .096$, $SE = .049$, $p = .050$). These results support Hypothesis 1 and possibly Hypothesis 2, but again, they are inconsistent across time lags.

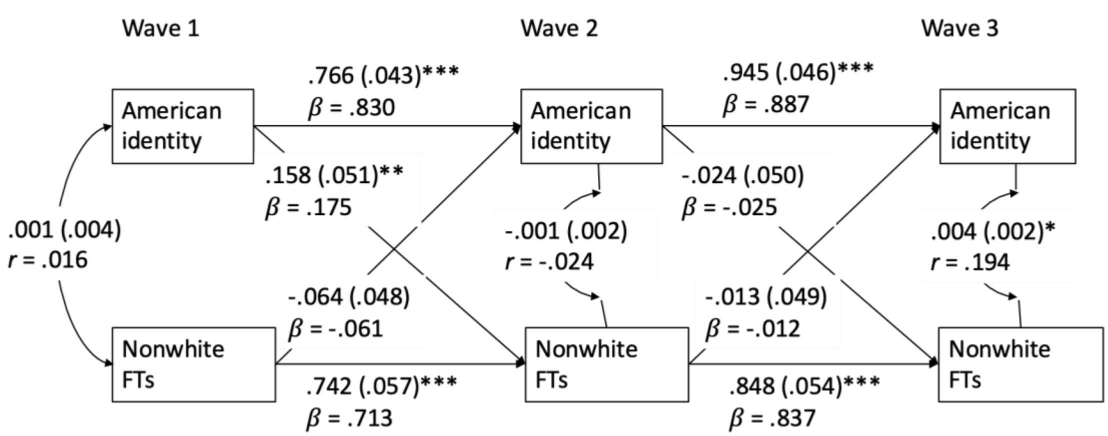
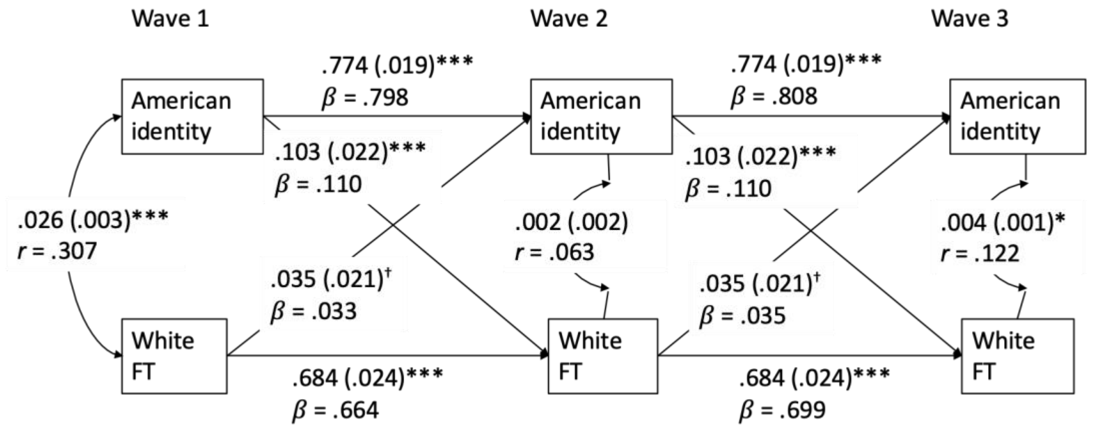


Figure 28. Study 2 CLPM for Latino respondents' American identity and nonwhite FTs, without covariates and with no stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Consistent with Hypothesis 1, American identity had positive cross-lagged effects on White FT ratings for Black respondents (*b* = .103, *SE* = .022, *p* < .001) in the model with stationarity and for Latino respondents from Wave 1 to Wave 2 (*b* = .226, *SE* = .053, *p* < .001) in the model without stationarity. (Figure 29 presents the CLPM results from the model with stationarity for Black respondents and the model without stationarity for Latino respondents.) These effects appear to be larger than the reverse effects from White FT ratings to American identity: In follow-up analyses, constraining the forward and reverse effects to be equal (in both waves in the model with stationarity for Black respondents and from Wave 1 to Wave 2 in the model without stationarity for Latino respondents) significantly worsened model fit (Black respondents: $\chi^2_8 = 172.008, \chi^2_9 = 176.778, \Delta\chi^2_1 = 4.770, p = .029$; Latino respondents: $\chi^2_4 = 42.039, \chi^2_5 = 48.055, \Delta\chi^2_1 = 6.016, p = .014$). Unexpectedly, however, racial identity (*b* = .056, *SE* = .024, *p* = .021) and POC identity (*b* = .058, *SE* = .023, *p* = .014) also had positive cross-lagged effects on White FT ratings (in the models with stationarity) among Black respondents. Neither of these identities showed significant cross-lagged relationships with White FT ratings among Latino respondents.

a.



b.

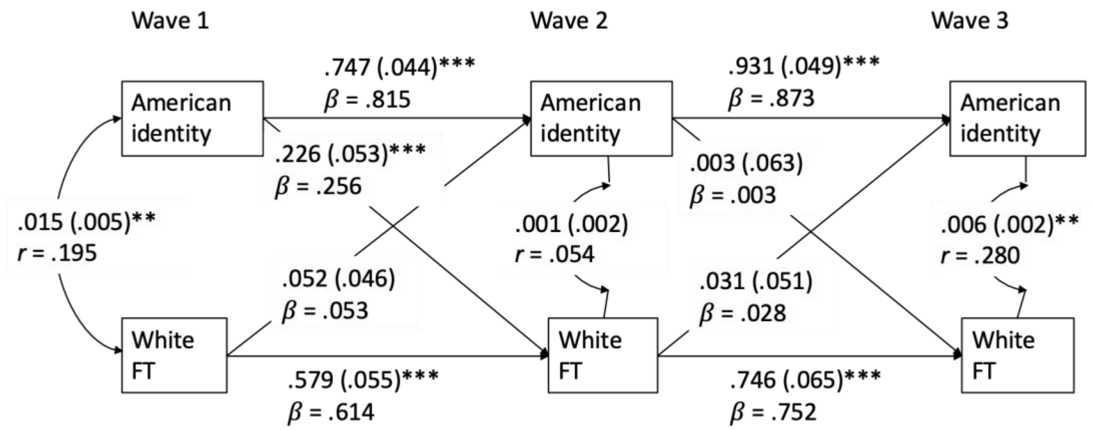


Figure 29. Study 2 CLPM for American identity and the White FT among Black respondents, with stationarity constraints on lagged and cross-lagged coefficients (a), and among Latino respondents, with no stationarity constraints (b). Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

b. Random-intercepts cross-lagged panel models. As was the case in Study 1, RI-CLPM showed better fit than CLPM for all identities and both nonwhite and White

FTs. All models met the Hu and Bentler (1999) criteria except Black respondents' American identity and nonwhite FTs without stationarity (RMSEA = .101), Latino respondents' American identity and nonwhite FTs with stationarity (RMSEA = .061), and Black respondents' POC identity and White FT without stationarity (RMSEA = .079). Stationarity significantly worsened model fit for Latino respondents' American identity and nonwhite FTs ($\chi^2_1 = 0.110, \chi^2_5 = 10.015, \Delta\chi^2_4 = 9.905, p = .042$) and marginally significantly worsened model fit for Latino respondents' American identity and White FTs ($\chi^2_1 = 0.309, \chi^2_5 = 8.657, \Delta\chi^2_4 = 8.348, p = .080$), as well as POC identity and nonwhite FTs among both Black ($\chi^2_1 = 2.399, \chi^2_5 = 10.708, \Delta\chi^2_4 = 8.309, p = .081$) and Latino ($\chi^2_1 = 0.412, \chi^2_5 = 8.617, \Delta\chi^2_4 = 8.205, p = .084$) respondents. Fit statistics are presented in Tables 29-32. Parameter estimates reported below are from the models without stationarity for Black respondents' POC identity and nonwhite FTs, Latino respondents' POC and American identities and nonwhite FTs, and Latino respondents' American identity and White FT; any other parameter estimates reported below are from the models with stationarity.

Trait-level covariances were significant and positive for POC identity and nonwhite FTs among both Black (c = .013, SE = .003, p < .001) and Latino (c = .020, SE = .005, p < .001) respondents, consistent with Hypothesis 2. However, American identity was significantly positively related to nonwhite FT ratings at the trait level only for Black respondents (c = .017, SE = .003, p < .001). Unexpectedly, racial identity was significantly positively related to nonwhite FT ratings for both groups (Black respondents: c = .012, SE = .003, p < .001; Latino respondents: c = .014, SE = .005, p = .010).

Consistent with Hypothesis 1, American identity was significantly positively related to White FT ratings at the trait level for both groups (Black respondents: $c = .024$, $SE = .003$, $p < .001$; Latino respondents: $c = .017$, $SE = .005$, $p = .001$); neither racial identity (Black respondents: $c = .001$, $SE = .003$, $p = .729$; Latino respondents: $c = .005$, $SE = .007$, $p = .465$) nor POC identity (Black respondents: $c = .004$, $SE = .003$, $p = .227$; Latino respondents: $c = -.001$, $SE = .005$, $p = .849$) was significantly related to White FT ratings. Thus, as expected, identification with a common ingroup that includes Whites is associated (at least at the between-person level) with more positive attitudes toward Whites, and identification with groups that do not include Whites are not significantly associated with attitudes toward Whites.

At the within-person level, neither racial identity nor POC identity significantly predicted nonwhite FT ratings over time. On the other hand, for Black respondents, American identity and nonwhite FT ratings had marginally significant to significant negative cross-lagged effects on each other (ID-FT: $b = -.124$, $SE = .071$, $p = .078$; FT-ID: $b = -.223$, $SE = .090$, $p = .013$) in the RI-CLPM with stationarity (Figure 30). For Latino respondents, American identity in Wave 1 had a positive cross-lagged effect on nonwhite FT ratings in Wave 2 ($b = .599$, $SE = .281$, $p = .033$) in the RI-CLPM without stationarity (Figure 31), but this effect is not present from Wave 2 to Wave 3, and the relatively small sample size and large standard errors suggest that the effect might not be reliable. Thus, if anything, it is American identity that appears to relate to attitudes toward other racial minorities over time at the within-person level, and for African Americans, that relationship could well be negative, despite the positive between-person relationship.

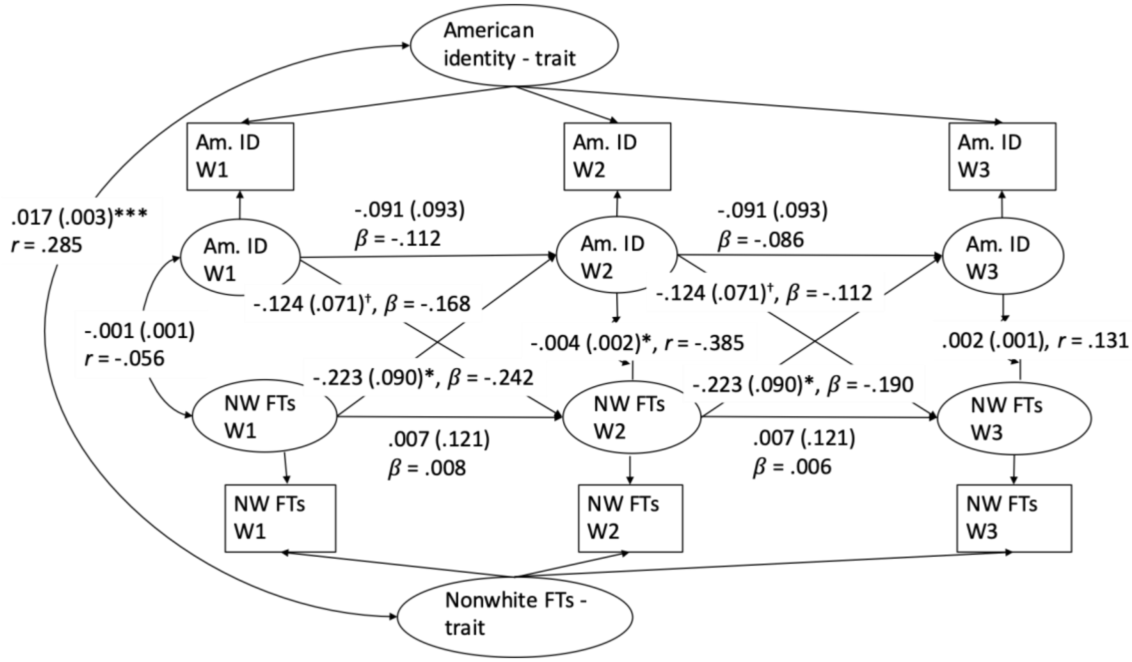


Figure 30. Study 2 RI-CLPM for Black respondents' American identity and nonwhite FTs, with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

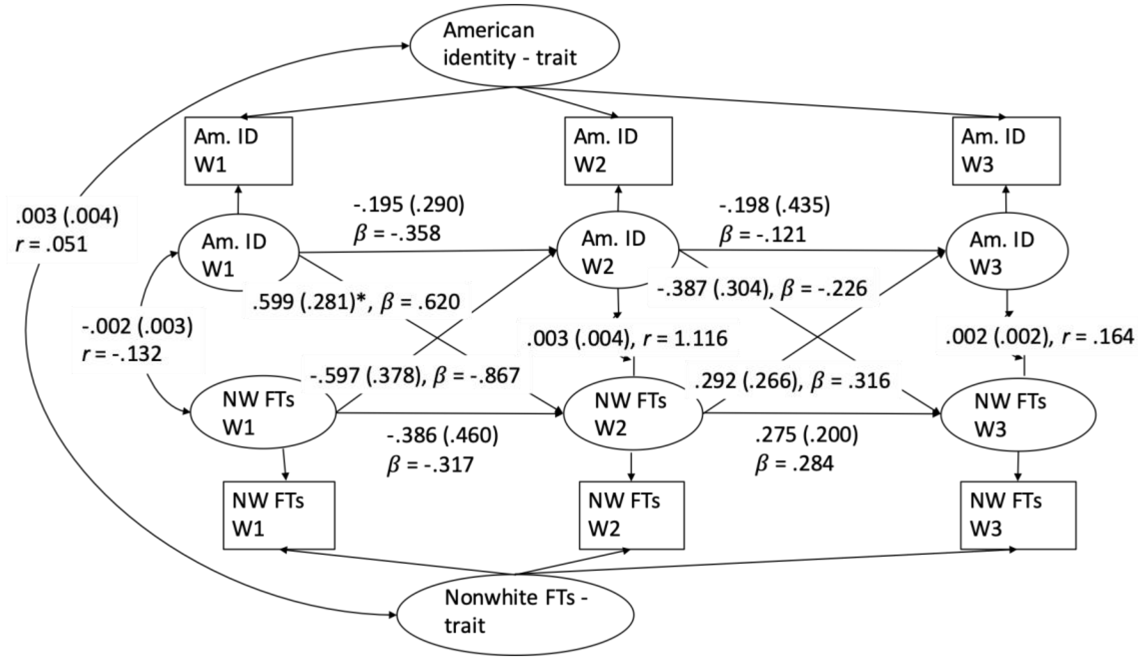


Figure 31. Study 2 RI-CLPM for Latino respondents' American identity and nonwhite FTs), with no stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Despite the positive trait-level association between American identity and White FT ratings, Black respondents showed no significant cross-lagged effects between these variables in the RI-CLPM, and Latino respondents showed a positive effect of Wave 1 identity on Wave 2 FT ratings (b = .581, SE = .236, p = .014) but a marginally significant (though larger in absolute magnitude) negative effect of Wave 2 identity on Wave 3 FT ratings (b = -.884, SE = .485, p = .068) in the RI-CLPM without stationarity (Figure 32). Additionally, Black respondents showed an unexpected positive cross-lagged effect of racial identity on White FT ratings in the RI-CLPM with stationarity (b = .225, SE = .102, p = .028) (Figure 33). This pattern of effects does not support Hypothesis 1 at the within-person level.

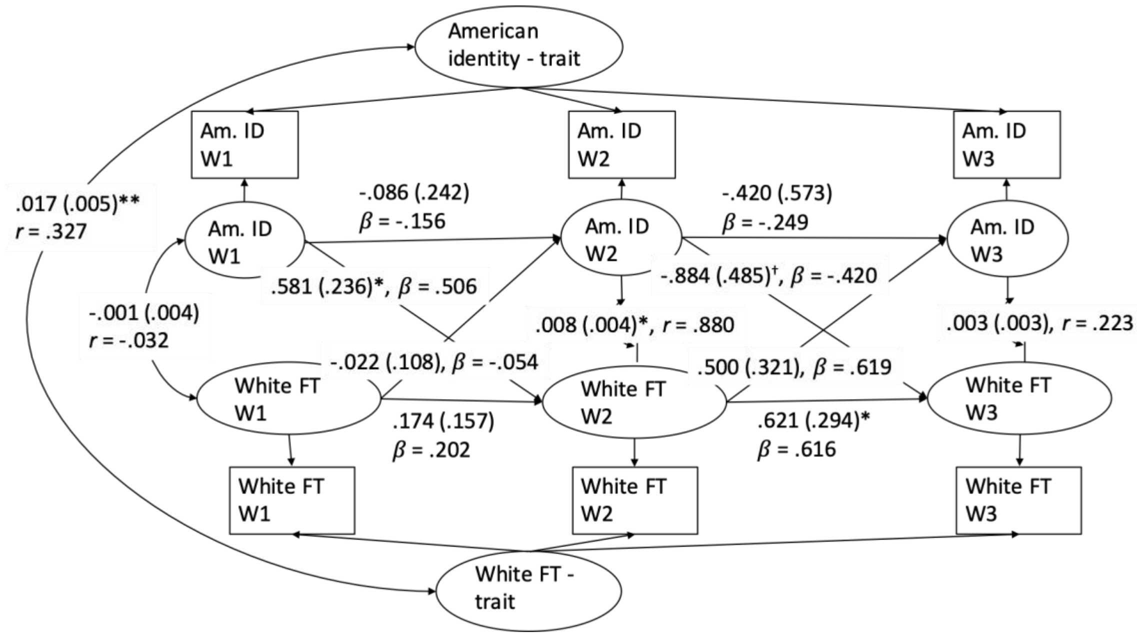


Figure 32. Study 2 RI-CLPM for Latino respondents' American identity and White FT, with no stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** p < .001, ** p < .01, * p < .05, † p < .10 (marginally significant).

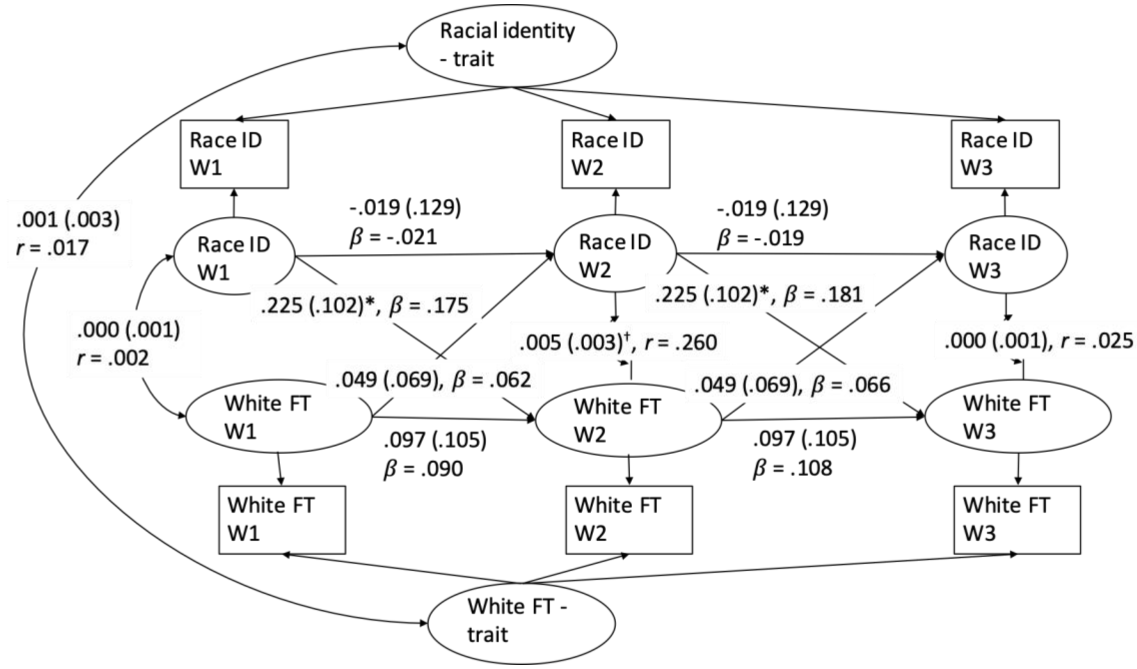


Figure 33. Study 2 RI-CLPM for Black respondents' racial identity and the White FT, with stationarity constraints on lagged and cross-lagged effects. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

3. Identity and Policy Attitudes

a. Immigration. I expected immigration to be an own-group issue area for Latino Americans, both because many of them are immigrants or have immediate family who are immigrants and because elite discourse on immigration tends to associate immigrants with Latinos. Thus, among Latino respondents, I expected racial identity to predict more liberal immigration attitudes (allowing more immigrants and favoring ending criminal penalties for illegal border-crossing) (Hypothesis 17) and American identity to predict less liberal immigration attitudes (Hypothesis 13). By contrast, I expected immigration to be an other-group issue area for a majority of African Americans (though with the potential exception of refugees from predominantly Muslim countries). Thus, among Black respondents, I expected POC identity, rather than racial identity, to predict more liberal immigration attitudes (Hypothesis 19) and American identity to predict less liberal immigration attitudes (Hypothesis 13).

Latino respondents. CLPM models showed adequate fit based on SRMR (≤ .08). For the models with the number of immigrants item, although CFI approached the fit criteria for the racial attitude models with covariates (CFI = .936), the CFI and RMSEA fit criteria were not met (CFI = .843-.936, RMSEA = .160-.284). With the decriminalizing immigration item, the racial identity models met the CFI fit criterion (CFI ≥ .952), and the American identity models approached this criterion (CFI = .913-.946). But RMSEA did not indicate adequate fit for any of these models (RMSEA = .086-.238), and CFI indicated poor fit for the POC identity models (CFI = .806-.880). Stationarity significantly worsened fit in almost all CLPM models with the number of immigrants item but did not significantly affect fit for any of the models with the decriminalizing immigration item, though the American identity model without covariates fit marginally significantly worse with stationarity ($\chi^2_4 = 36.365, \chi^2_8 = 45.532, \Delta\chi^2_4 = 9.167, p = .057$). Thus, CLPM parameter estimates reported below are from models without stationarity except for racial and POC identities and decriminalizing immigration.

RI-CLPM fit significantly better than CLPM for all 3 identities and both immigration items, and the RI-CLPM models without stationarity met all 3 fit criteria. However, the sample size of Latino respondents in this study is relatively small (total N = 272; 120 completed all 3 waves), so I did not have the statistical power to reliably detect cross-lagged effects in the RI-CLPM, at least without assuming stationarity. Stationarity significantly worsened fit for racial and American identities and number of immigrants (racial identity: $\chi_1^2 = 0.049, \chi_5^2 = 10.488, \Delta\chi_4^2 = 10.439, p = .034$; American identity: $\chi_1^2 = 0.867, \chi_5^2 = 11.122, \Delta\chi_4^2 = 10.255, p = .036$) and produced a warning in the racial identity model that the variance-covariance matrix of latent variables was not positive definite. Fit statistics are presented in Tables 33 and 34.

Table 33

Study 2 Panel Model Fit Statistics: Immigration Attitudes (Number of Immigrants), Latino Respondents

	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
Racial ID					
CLPM no covariates	.908	.226	.049	59.708 (4)***	
CLPM no cov w/ stationarity	.901	.165	.061	67.460 (8)***	7.752 (4)
CLPM w/ covariates	.931	.233	.025	63.172 (4)***	
CLPM w/ cov w/ stationarity	.922	.175	.033	74.619 (8)***	11.447 (4)*
RI-CLPM	1.000	.000	.003	0.049 (1)	59.659 (3)***
RI-CLPM w/ stationarity	.991	.064	.046	10.488 (5)†	10.439 (4)*
POC ID					
CLPM no covariates	.850	.275	.065	86.495 (4)***	
CLPM no cov w/ stationarity	.843	.200	.077	94.760 (8)***	8.265 (4)†
CLPM w/ covariates	.893	.284	.033	91.805 (4)***	
CLPM w/ cov w/ stationarity	.882	.211	.042	104.929 (8)***	13.124 (4)*
RI-CLPM	1.000	.009	.014	1.020 (1)	
RI-CLPM w/ stationarity	.994	.050	.041	8.447 (5)	7.427 (4)

American ID					
CLPM no covariates	.895	.257	.053	75.836 (4)***	
CLPM no cov w/ stationarity	.884	.192	.087	87.978 (8)***	12.142 (4)*
CLPM w/ covariates	.917	.275	.028	86.406 (4)***	
CLPM w/ cov w/ stationarity	.902	.211	.044	105.324 (8)***	18.918 (4)***
RI-CLPM	1.000	.000	.012	0.867 (1)	74.969 (3)***
RI-CLPM w/ stationarity	.991	.067	.043	11.122 (5)*	10.255 (4)*

Note: N = 272 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 34

Study 2 Panel Model Fit Statistics: Immigration Attitudes (Ending Criminal Penalties for Illegal Immigration), Latino Respondents

	CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
Racial ID					
CLPM no covariates	.952	.127	.042	21.439 (4)***	
CLPM no cov w/ stationarity	.956	.086	.050	23.974 (8)**	2.535 (4)
CLPM w/ covariates	.966	.129	.022	22.137 (4)***	
CLPM w/ cov w/ stationarity	.968	.089	.026	25.067 (8)**	2.930 (4)
RI-CLPM	1.000	.000	.019	0.644 (1)	20.795 (3)***
RI-CLPM w/ stationarity	1.000	.000	.025	2.035 (5)	1.391 (4)
POC ID					
CLPM no covariates	.810	.231	.063	62.031 (4)***	
CLPM no cov w/ stationarity	.806	.165	.075	67.000 (8)***	4.969 (4)
CLPM w/ covariates	.880	.238	.033	65.403 (4)***	
CLPM w/ cov w/ stationarity	.874	.172	.040	72.210 (8)***	6.807 (4)

RI-CLPM	1.000	.000	.014	0.354 (1)	61.677 (3)***
RI-CLPM w/ stationarity	1.000	.000	.034	4.814 (5)	4.460 (4)
American ID					
CLPM no covariates	.925	.172	.045	36.365 (4)***	
CLPM no cov w/ stationarity	.913	.131	.064	45.532 (8)***	9.167 (4)†
CLPM w/ covariates	.946	.181	.025	39.561 (4)***	
CLPM w/ cov w/ stationarity	.941	.134	.029	47.096 (8)***	7.535 (4)
RI-CLPM	1.000	.000	.010	0.206 (1)	36.159 (3)***
RI-CLPM w/ stationarity	1.000	.001	.039	5.003 (5)	4.797 (4)

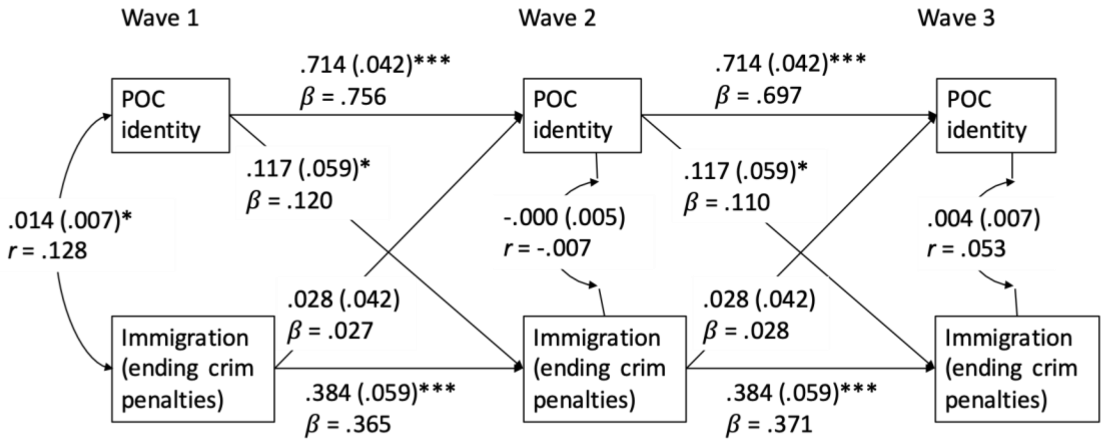
Note: N = 272 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Contrary to Hypothesis 17, racial identity did not have significant cross-lagged effects on Latino respondents' attitudes about the number of immigrants who should be allowed into the U.S., at least in the CLPM. In the RI-CLPM without stationarity, neither the within-person cross-lagged effects nor the trait-level covariance were significant. The RI-CLPM with stationarity did show a marginally significant positive trait-level covariance between racial identity and attitudes about the number of immigrants (b = .009, SE = .005, p = .060), as well as significant positive cross-lagged effects in both directions (ID-attitude: b = .330, SE = .168, p = .050; attitude-ID: b = .263, SE = .115, p = .022); however, this model not only fit significantly worse than the model without stationarity but also produced a warning that the covariance matrix of latent variables was not positive definite, and these observations, along with the small sample size, caution against relying on these results. Racial identity had no significant cross-lagged effects or trait-level covariance with attitudes toward ending criminal penalties for illegal border crossing. Thus, overall, these results do not support Hypothesis 17 that racial identity would predict more liberal immigration attitudes among Latino Americans.

On the other hand, POC identity showed a significant positive trait-level covariance with preference for allowing more immigrants in the RI-CLPM with stationarity (c = .027, SE = .005, p < .001) and, more importantly, a significant cross-lagged effect on support for ending criminal penalties for immigration that appeared in both the CLPM without covariates (and with stationarity) (b = .117, SE = .059, p = .047) and the RI-CLPM (with stationarity) (b = .430, SE = .198, p = .030) (The CLPM and RI-CLPM results are illustrated in Figure 34). In the CLPM without stationarity, POC identity in Wave 1 had a significant positive cross-lagged effect on preference for allowing more immigrants into the U.S. in Wave 2 (b = .105, SE = .051, p = .042), though the reverse effect was also positive and significant (b = .187, SE = .067, p = .005) (Figure 35); no significant cross-lagged effects appeared in the RI-CLPM. Taken together, these effects suggest that for Latino Americans, as for Asian Americans, it might be POC identity rather than racial identity that connects to immigration attitudes.

a.



b.

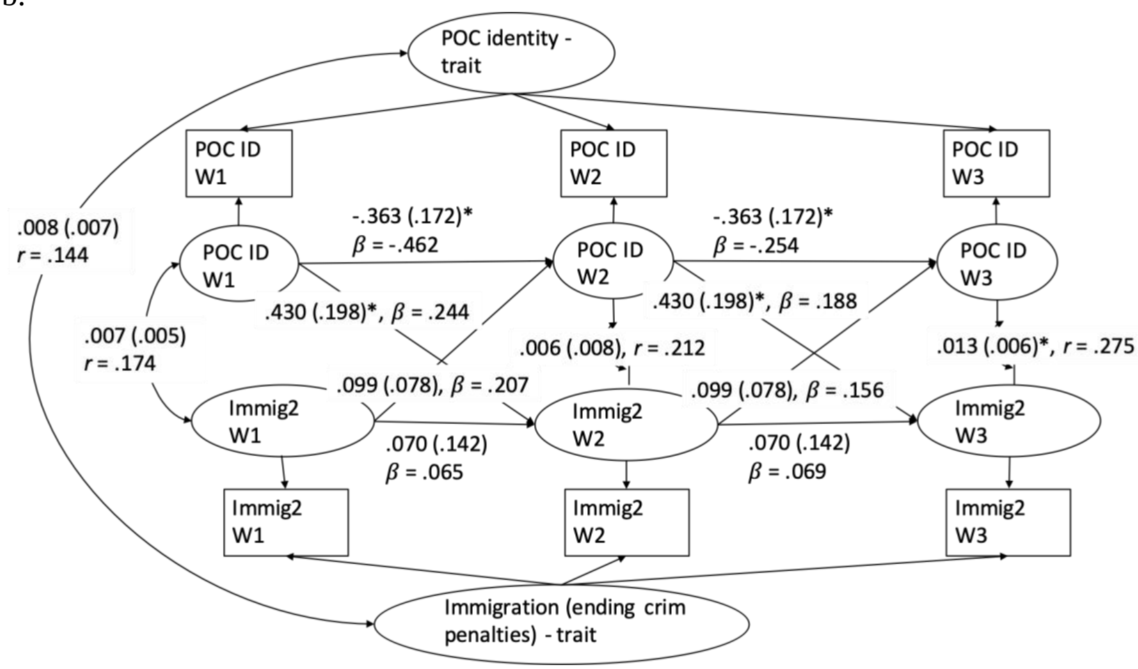


Figure 34. Study 2 CLPM (without covariates) (a) and RI-CLPM (b) for Latino respondents' POC identity and support for ending criminal penalties for illegal immigration. Both models include stationarity constraints on lagged and cross-lagged effects. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

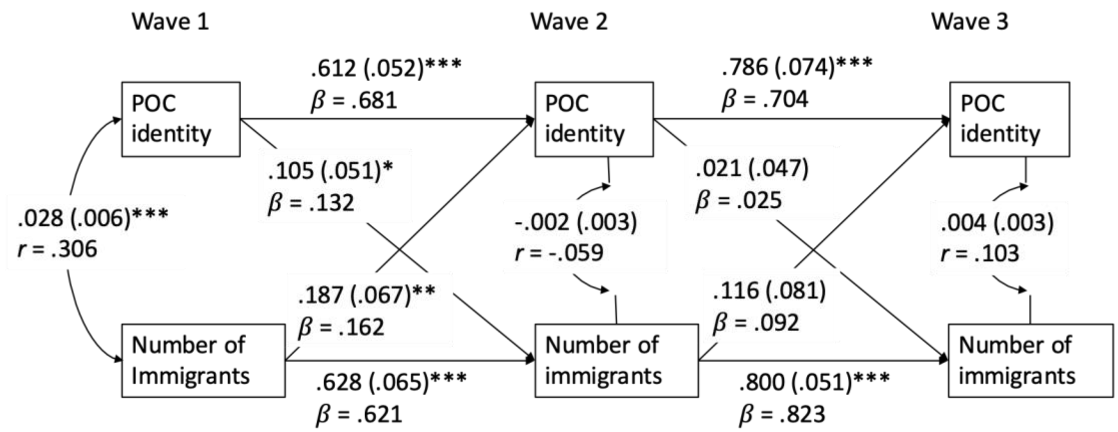
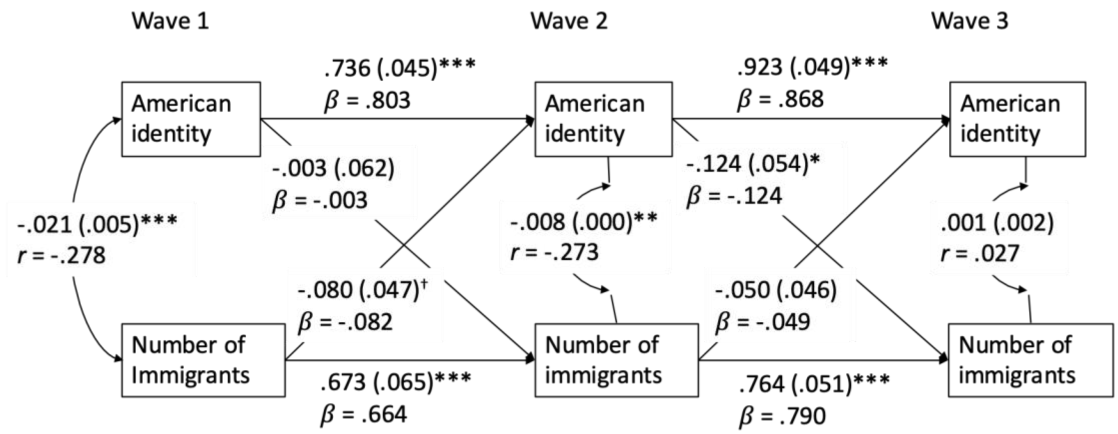


Figure 35. Study 2 CLPM for Latino respondents' POC identity and attitudes toward the number of immigrants who should be allowed into the U.S., without covariates and with no stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

By contrast, American identity related to Latino respondents' immigration attitudes in ways that are consistent with Hypothesis 13. In the CLPM (without stationarity), American identity had a significant negative cross-lagged effect over at least one time lag on preference for allowing more immigrants (W2-W3 $b = -.124$, $SE = .054$, $p = .021$) and support for ending criminal penalties for immigration (W1-W2 $b = -.209$, $SE = .088$, $p = .017$) (Figure 36). And American identity had a significant negative trait-level covariance with both immigration items in the RI-CLPM (number of immigrants: $c = -.023$, $SE = .005$, $p < .001$; ending criminal penalties: $c = -.013$, $SE = .005$, $p = .014$, both models without stationarity), though none of the cross-lagged coefficients were significant in the RI-CLPM.

a.



b.

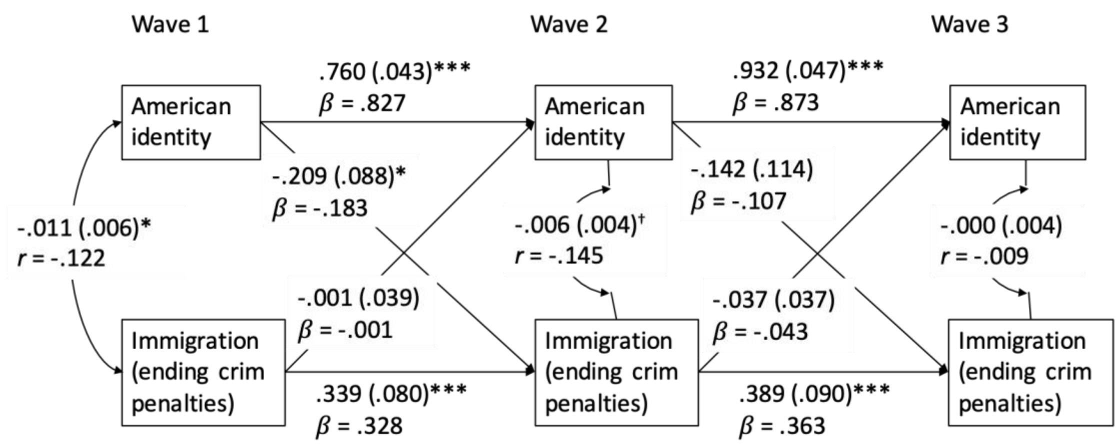


Figure 36. Study 2 CLPM for Latino respondents' American identity and attitudes toward the number of immigrants who should be allowed into the U.S. (a) and ending criminal penalties for illegal immigration (b). Models do not include covariates or stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Black respondents. CLPM models once again showed adequate fit based on SRMR (.025-.058) but not CFI (.894-.946) or RMSEA (.116-.266). Stationarity did not significantly affect model fit except for the model with American identity and ending criminal penalties, without covariates ($\chi^2_4 = 128.758, \chi^2_8 = 139.285, \Delta\chi^2_4 = 10.527, p = .032$); for the model with covariates, stationarity marginally significantly worsened fit ($\chi^2_4 = 119.093, \chi^2_8 = 127.641, \Delta\chi^2_4 = 8.548, p = .073$). RI-CLPM improved model fit across the board, and all RI-CLPM models met the Hu and Bentler (1999) fit criteria. Stationarity did not significantly affect RI-CLPM model fit. Fit statistics are presented in Tables 35 and 36. Parameter estimates reported below are from the models with stationarity except for the CLPM with American identity and ending criminal penalties.

Table 35

Study 2 Panel Model Fit Statistics: Immigration Attitudes (Number of Immigrants), Black Respondents

	CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
Racial ID					
CLPM no covariates	.899	.256	.055	176.318 (4)***	
CLPM no cov w/ stationarity	.900	.180	.056	178.936 (8)***	2.618 (4)
CLPM w/ covariates	.921	.252	.027	171.106 (4)***	
CLPM w/ cov w/ stationarity	.922	.177	.028	173.075 (8)***	1.969 (4)
RI-CLPM	1.000	.000	.005	0.367 (1)	175.951 (3)***
RI-CLPM w/ stationarity	1.000	.012	.017	5.466 (5)	5.079 (4)
POC ID					
CLPM no covariates	.921	.226	.050	138.417 (4)***	
CLPM no cov w/ stationarity	.919	.161	.053	144.891 (8)***	6.474 (4)

CLPM w/ covariates	.936	.226	.025	138.103 (4)***	
CLPM w/ cov w/ stationarity	.936	.160	.026	142.769 (8)***	4.666 (4)
RI-CLPM	1.000	.000	.007	0.881 (1)	137.536 (3)***
RI-CLPM w/ stationarity	.998	.031	.023	8.258 (5)	7.377 (4)
American ID					
CLPM no covariates	.897	.266	.055	190.770 (4)***	
CLPM no cov w/ stationarity	.895	.190	.058	197.786 (8)***	7.016 (4)
CLPM w/ covariates	.924	.254	.026	173.710 (4)***	
CLPM w/ cov w/ stationarity	.923	.181	.027	180.208 (8)***	6.498 (4)
RI-CLPM	1.000	.000	.001	0.021 (1)	190.749 (3)***
RI-CLPM w/ stationarity	1.000	.000	.014	3.987 (5)	3.966 (4)

Note: N = 658 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 36

Study 2 Panel Model Fit Statistics: Immigration Attitudes (Ending Criminal Penalties for Illegal Immigration), Black Respondents

	CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
Racial ID					
CLPM no covariates	.901	.203	.054	112.131 (4)***	
CLPM no cov w/ stationarity	.901	.143	.055	115.836 (8)***	3.705 (4)
CLPM w/ covariates	.926	.203	.028	112.127 (4)***	
CLPM w/ cov w/ stationarity	.925	.144	.028	116.768 (8)***	4.641 (4)
RI-CLPM	1.000	.019	.013	1.237 (1)	110.894 (3)***
RI-CLPM w/ stationarity	1.000	.000	.015	3.867 (5)	2.630 (4)
POC ID					

CLPM no covariates	.931	.167	.049	77.277 (4)***	
CLPM no cov w/ stationarity	.933	.116	.050	79.217 (8)***	1.940 (4)
CLPM w/ covariates	.946	.172	.026	82.186 (4)***	
CLPM w/ cov w/ stationarity	.946	.122	.026	85.900 (8)***	3.714 (4)
RI-CLPM	1.000	.000	.002	0.057 (1)	77.220 (3)***
RI-CLPM w/ stationarity	1.000	.000	.013	2.736 (5)	2.679 (4)
American ID					
CLPM no covariates	.899	.218	.052	128.758 (4)***	
CLPM no cov w/ stationarity	.894	.158	.056	139.285 (8)***	10.527 (4)*
CLPM w/ covariates	.929	.209	.026	119.093 (4)***	
CLPM w/ cov w/ stationarity	.926	.151	.027	127.641 (8)***	8.548 (4)†
RI-CLPM	1.000	.000	.007	0.347 (1)	128.411 (3)***
RI-CLPM w/ stationarity	1.000	.000	.018	4.271 (5)	3.924 (4)

Note: N = 658 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Consistent with Hypothesis 19, POC identity had significant positive cross-lagged effects on preference for allowing more immigrants in the CLPM (b = .072, SE = .023, p = .002) and marginally significant positive cross-lagged effects in the RI-CLPM (b = .158, SE = .093, p = .090) (Figure 41). However, the reverse effect, from preference for allowing more immigrants to POC identity, was also significant in the CLPM (b = .065, SE = .022, p = .003). POC identity had a significant positive trait-level covariance, in the RI-CLPM, with both preference for allowing more immigrants (c = .014, SE = .003, p < .001) and support for ending criminal penalties for immigration (c = .006, SE = .003, p =

.048). None of the cross-lagged effects were significant in the models with POC identity and ending criminal penalties for immigration.

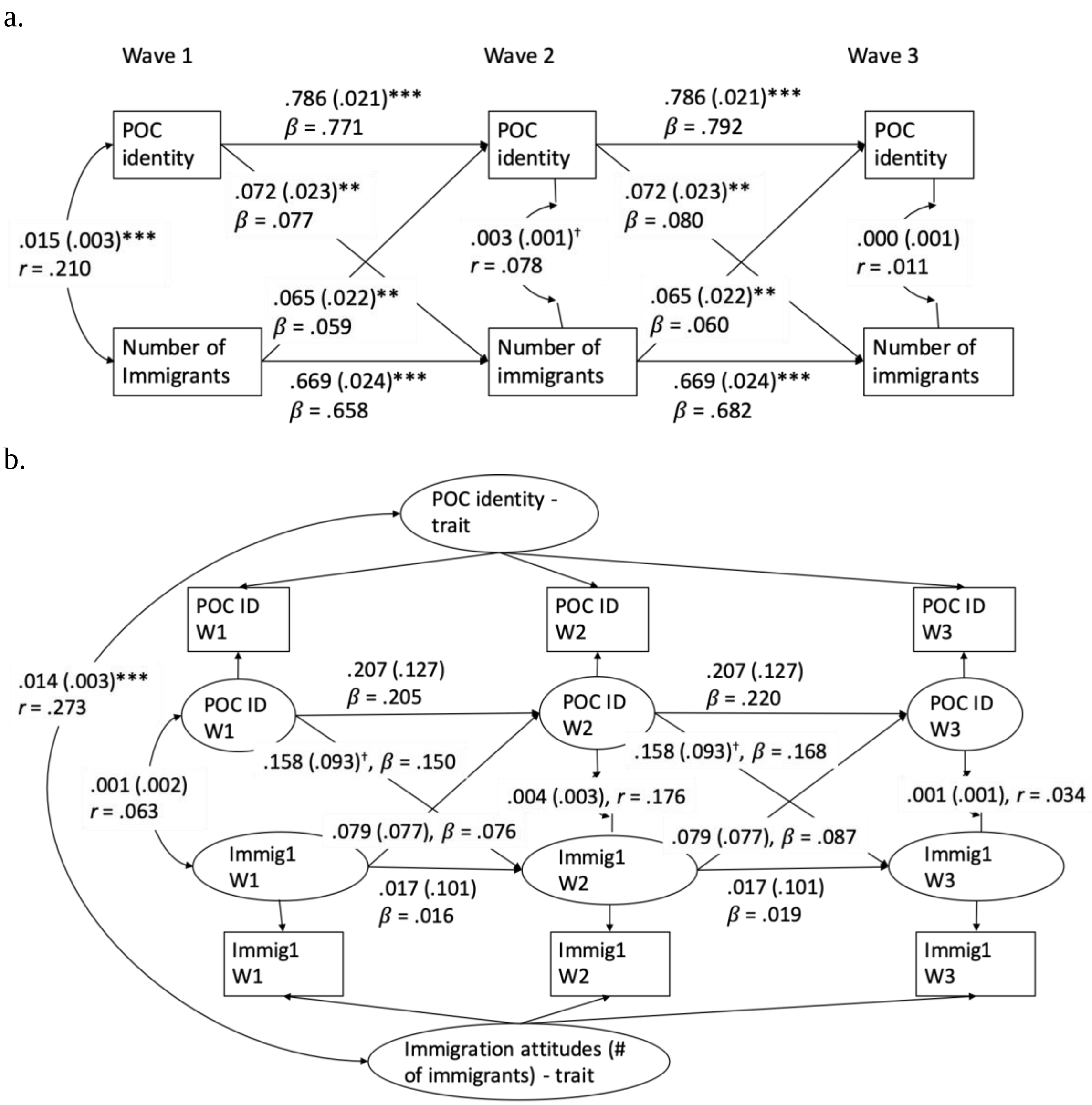


Figure 37. Study 2 CLPM (without covariates) (a) and RI-CLPM (b) for Black respondents' POC identity and attitudes toward the number of immigrants who should be allowed into the U.S. Models include stationarity constraints on lagged and cross-lagged effects. Unstandardized coefficients with standard errors (in parentheses) and

standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Not only was POC identity associated with more liberal immigration attitudes among Black respondents, however, but so was racial identity, which I did not expect to be associated with attitudes toward an other-group issue. Like POC identity, racial identity had a significant positive trait-level covariance with both immigration items (number of immigrants: $c = .013$, $SE = .003$, $p < .001$; ending criminal penalties: $c = .007$, $SE = .003$, $p = .007$). In the CLPM (Figure 42), racial identity and preference for allowing more immigrants had significant positive cross-lagged effects on each other (ID-attitude: $b = .049$, $SE = .024$, $p = .037$; attitude-ID: $b = .082$, $SE = .021$, $p < .001$). These effects are particularly striking compared to the lack of racial identity effects among Latino respondents.

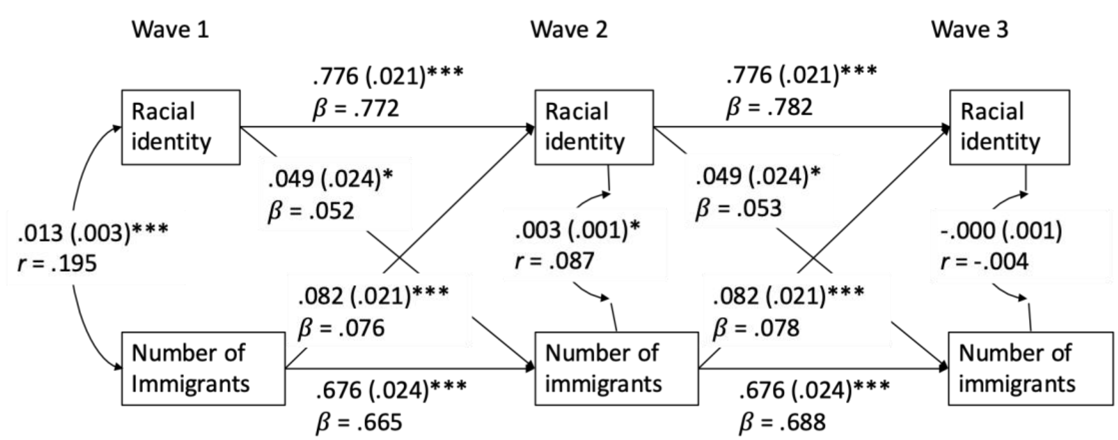


Figure 38. Study 2 CLPM for Black respondents' racial identity and attitudes toward the number of immigrants who should be allowed into the U.S. Model does not include

covariates and does include stationarity constraints on lagged and cross-lagged effects. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Consistent with Hypothesis 13, American identity had a significant negative trait covariance with support for ending criminal penalties for immigration (c = -.006, SE = .003, p = .043) and a marginally significant negative (within-person) cross-lagged effect on responses to that item (b = -.200, SE = .119, p = .093) in the RI-CLPM (Figure 39). The cross-lagged effects were not significant in the CLPM without stationarity, however, and stationarity significantly worsened CLPM model fit. Contrary to Hypothesis 13, American identity showed no significant relationship with preference for allowing more immigrants into the U.S. Thus, support for Hypothesis 13 was mixed among Black respondents.

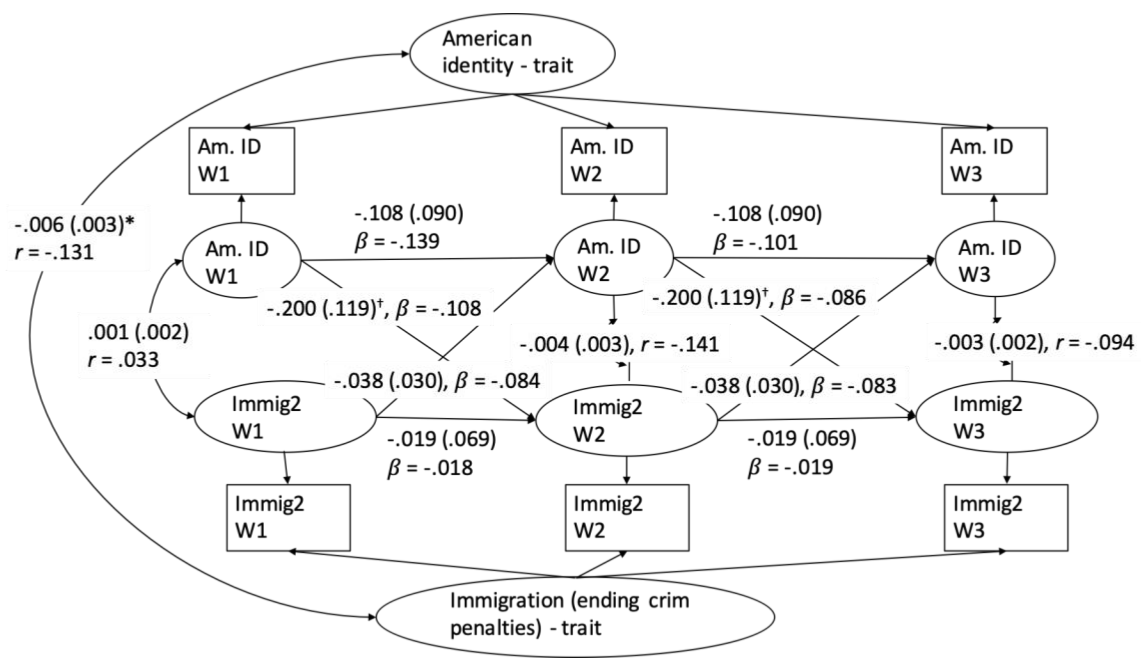


Figure 39. Study 2 RI-CLPM for Black respondents' American identity and support for ending criminal penalties for illegal immigration, with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

b. Criminal justice reform. Considering the focus on African Americans in the current discourse on criminal justice reform, I expected this to be an own-group issue for Black respondents and an other-group issue for Latino respondents (even though some evidence suggests that the criminal justice system might also be biased against Latinos). Accordingly, I expected racial identity to predict more support for criminal justice reform among Black respondents (Hypothesis 18), POC identity to predict more support for criminal justice reform among Latino respondents (Hypothesis 20), and American identity to predict less support for criminal justice reform among both respondent groups (Hypothesis 13).

Support for criminal justice reform was operationalized as higher scores on the Black Lives Matter/George Floyd protests composite variable (indicating more support for BLM and the protests) or choosing the response that a judge should have the freedom to give a shorter sentence than the mandatory minimum. I initially treated the mandatory minimum sentence item as a categorical variable in the CLPM. However, model specifications for the RI-CLPM would not accommodate a categorical variable; thus, I re-ran the CLPM, treating the mandatory minimum sentence variable as continuous, to enable comparisons between the CLPM and RI-CLPM.

Black respondents. Fit statistics are presented in Tables 37 and 38. CLPM models for the BLM/protests composite variable met the fit criteria for SRMR (.015-.040) and met or nearly met the fit criteria for CFI (.936-.966) but did not meet the criteria for RMSEA (.143-.251). Models treating the mandatory minimum sentence model as continuous met the fit criteria for SRMR (.028-.068) but not CFI (.884-.940) or RMSEA (.140-.237); models treating this variable as categorical, on the other hand, met the criterion for CFI based on the non-robust version (CFI = .964-.984) but not the robust version (CFI = .860-.937), met the criterion for SRMR only when covariates were included (with covariates: SRMR = .066-.073; without covariates: SRMR = .157-.162), and still did not meet the criterion for RMSEA (non-robust RMSEA = .064-.109; robust RMSEA = .104-.174). Stationarity did not significantly affect CLPM model fit in models with the BLM/protests variable, but it did significantly reduce model fit in the racial identity (without covariates: $\chi^2_4 = 144.466, \chi^2_8 = 154.033, \Delta\chi^2_4 = 9.567, p = .048$; with covariates: $\chi^2_4 = 139.064, \chi^2_8 = 147.458, \Delta\chi^2_4 = 8.394, p = .078$) and American identity (without covariates: $\chi^2_4 = 151.595, \chi^2_8 = 168.325, \Delta\chi^2_4 = 16.730, p = .002$; with covariates: $\chi^2_4 = 137.654, \chi^2_8 = 147.598, \Delta\chi^2_4 = 9.944, p = .041$) models with the mandatory minimum sentence variable treated as continuous.

RI-CLPM significantly improved model fit over CLPM, and fit statistics indicated good fit for all RI-CLPM models. Stationarity marginally significantly worsened RI-CLPM model fit for the BLM/protests variable and racial ($\chi^2_1 = 0.113, \chi^2_5 = 9.390, \Delta\chi^2_4 = 9.277, p = .055$) and American ($\chi^2_1 = 0.099, \chi^2_5 = 8.476, \Delta\chi^2_4 = 8.377, p = .079$) identities and the mandatory minimum sentence variable and POC

($\chi_1^2 = 0.086, \chi_5^2 = 7.966, \Delta\chi_4^2 = 7.880, p = .096$) and American ($\chi_1^2 = 0.017, \chi_5^2 = 9.312, \Delta\chi_4^2 = 9.295, p = .054$) identities.

Table 37

Study 2 Panel Model Fit Statistics: Criminal Justice Attitudes (BLM/Protests), Black Respondents

	CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
Racial ID					
CLPM no covariates	.949	.229	.035	142.442 (4)***	
CLPM no cov w/ stationarity	.949	.162	.038	146.607 (8)***	4.165 (4)
CLPM w/ covariates	.959	.223	.018	134.309 (4)***	
CLPM w/ cov w/ stationarity	.958	.159	.020	140.701 (8)***	6.392 (4)
RI-CLPM	1.000	.000	.002	0.113 (1)	142.329 (3)***
RI-CLPM w/ stationarity	.998	.037	.022	9.390 (5)†	9.277 (4)†
POC ID					
CLPM no covariates	.958	.205	.030	114.341 (4)***	
CLPM no cov w/ stationarity	.958	.146	.031	119.808 (8)***	5.467 (4)
CLPM w/ covariates	.966	.201	.015	110.400 (4)***	
CLPM w/ cov w/ stationarity	.966	.143	.016	115.391 (8)***	4.991 (4)
RI-CLPM	1.000	.000	.001	0.007 (1)	114.334 (3)***
RI-CLPM w/ stationarity	1.000	.010	.015	5.345 (5)	5.338 (4)
American ID					
CLPM no covariates	.937	.251	.036	169.780 (4)***	
CLPM no cov w/ stationarity	.936	.179	.040	176.056 (8)***	6.276 (4)
CLPM w/ covariates	.954	.237	.017	151.926 (4)***	
CLPM w/ cov w/ stationarity	.954	.168	.018	156.129 (8)***	4.203 (4)

RI-CLPM	1.000	.000	.002	0.099 (1)	169.681 (3)***
RI-CLPM w/ stationarity	.999	.033	.019	8.476 (5)	8.377 (4)†

Note: N = 658 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 38

Study 2 Panel Model Fit Statistics: Criminal Justice Attitudes (Mandatory Minimum Sentence), Black Respondents

	CFI	**RMSEA**	**SRMR**	**χ^2 (df)**	**$\Delta\chi^2$ (df)**
Racial ID, continuous DV					
CLPM no covariates	.888	.231	.064	144.466 (4)***	
CLPM no cov w/ stationarity	.884	.167	.068	154.033 (8)***	9.567 (4)*
CLPM w/ covariates	.919	.227	.031	139.064 (4)***	
CLPM w/ cov w/ stationarity	.916	.163	.033	147.458 (8)***	8.394 (4)†
RI-CLPM	1.000	.000	.005	0.247 (1)	144.219 (3)***
RI-CLPM w/ stationarity	.998	.024	.024	6.966 (5)	6.719 (4)
Racial ID, categorical DV					
CLPM no covariates	.967/.865	.109/.174	.157	35.374 (4)***	
CLPM no cov w/ stationarity	.968/.893	.075/.109	.157	37.799 (8)***	2.425 (4)
CLPM w/ covariates	.983/.924	.095/.165	.072	27.492 (4)***	
CLPM w/ cov w/ stationarity	.984/.935	.066/.108	.068	31.186 (8)***	3.694 (4)
POC ID					
CLPM no covariates	.918	.196	.059	105.009 (4)***	

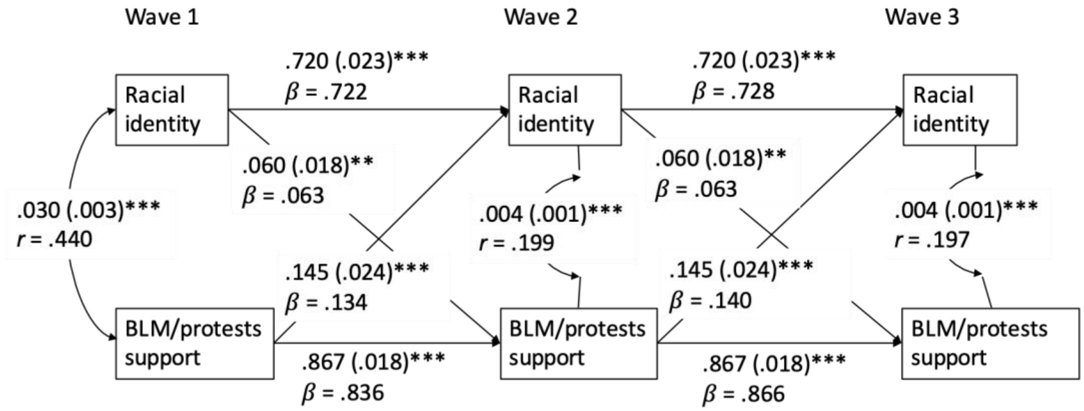
CLPM no cov w/ stationarity	.916	.140	.063	111.882 (8)***	6.873 (4)
CLPM w/ covariates	.940	.194	.028	102.972 (4)***	
CLPM w/ cov w/ stationarity	.938	.140	.030	110.554 (8)***	7.582 (4)
RI-CLPM	1.000	.000	.003	0.086 (1)	104.923 (3)***
RI-CLPM w/ stationarity	.998	.030	.024	7.966 (5)	7.880 (4)†
POC ID, categorical DV					
CLPM no covariates	.967/.865	.108/.173	.159	34.432 (4)***	
CLPM no cov w/ stationarity	.970/.899	.073/.106	.158	35.832 (8)***	1.400 (4)
CLPM w/ covariates	.984/.925	.093/.163	.073	26.513 (4)***	
CLPM w/ cov w/ stationarity	.984/.937	.064/.106	.069	29.865 (8)***	3.352 (4)
American ID					
CLPM no covariates	.894	.237	.059	151.595 (4)***	
CLPM no cov w/ stationarity	.885	.175	.067	168.325 (8)***	16.730 (4)**
CLPM w/ covariates	.926	.225	.028	137.654 (4)***	
CLPM w/ cov w/ stationarity	.923	.163	.031	147.598 (8)***	9.944 (4)*
RI-CLPM	1.000	.000	.001	0.017 (1)	151.578 (3)***
RI-CLPM w/ stationarity	.997	.036	.025	9.312 (5)†	9.295 (4)†
American ID, categorical DV					
CLPM no covariates	.967/.860	.106/.173	.160	33.304 (4)***	
CLPM no cov w/ stationarity	.964/.887	.078/.110	.162	39.898 (8)***	6.594 (4)
CLPM w/ covariates	.984/.928	.089/.156	.070	24.641 (4)***	
CLPM w/ cov w/ stationarity	.983/.937	.065/.104	.066	30.394 (8)***	5.753 (4)

Note: N = 658 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Racial identity had a significant positive trait-level covariance with support for BLM and the George Floyd protests (*c* = .032, *SE* = .003, *p* < .001, without stationarity) and with support for judicial discretion to give sentences below the mandatory minimum (*c* = .019, *SE* = .004, *p* < .001, with stationarity) in the RI-CLPM, consistent with Hypothesis 18. However, with the BLM/protests variable, significant cross-lagged effects appeared in both directions in the CLPM (with stationarity) (ID-attitude: *b* = .060, *SE* = .018, *p* = .001; attitude-ID: *b* = .145, *SE* = .024, *p* < .001), and only the reverse effect from Wave 2 attitude to Wave 3 identity was significant in the RI-CLPM (*b* = .356, *SE* = .150, *p* = .018) (Figure 40). In follow-up analyses, constraining identity-attitude and attitude-identity cross-lagged coefficients to be equal resulted in poorer model fit for the CLPM ($\chi_8^2 = 146.607, \chi_9^2 = 154.201, \Delta\chi_1^2 = 7.594, p = .006$), and constraining the Wave 2 to Wave 3 identity-attitude and attitude-identity cross-lagged coefficients to be equal resulted in poorer model fit for the RI-CLPM ($\chi_1^2 = 0.113, \chi_2^2 = 5.144, \Delta\chi_1^2 = 5.031, p = .025$). Thus, attitudes toward Black Lives Matter and the George Floyd protests appear to predict Black respondents' racial identity more strongly and consistently than racial identity predicts these attitudes, at both the between-person and within-person levels.

a.



b.

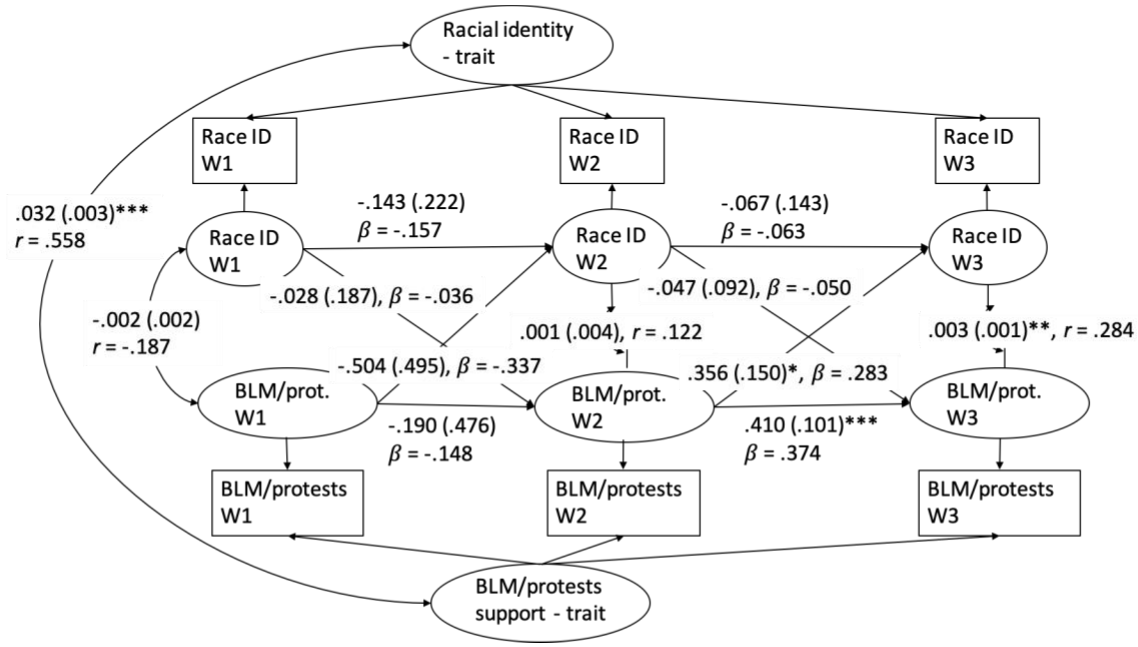
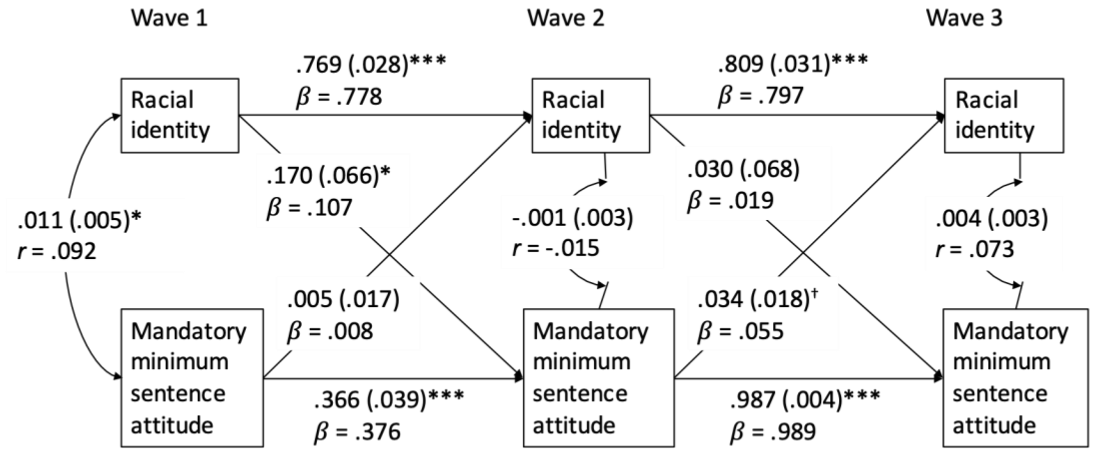


Figure 40. Study 2 CLPM (without covariates) with stationarity constraints on lagged and cross-lagged coefficients (a) and RI-CLPM with no stationarity constraints (b) for Black respondents' racial identity and support for Black Lives Matter and the George Floyd protests. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

With the mandatory minimum sentence variable, cross-lagged effects varied by model. When the mandatory minimum sentence variable was treated as continuous, the stationarity assumption was not met, and the CLPM without stationarity showed a significant cross-lagged effect of Wave 1 identity on Wave 2 attitude (b = .170, SE = .066, p = .010) but a marginally significant cross-lagged effect of Wave 2 attitude on Wave 3 identity (b = .034, SE = .018, p = .057). When the variable was treated as categorical, the stationarity assumption was met, and the CLPM with stationarity showed significant cross-lagged effects in both directions (ID-attitude: b = .365, SE = .146, p = .012; attitude-ID: b = .014, SE = .007, p = .036). However, at the within-person level, the RI-CLPM (with stationarity) showed significant *negative* cross-lagged effects in both directions (ID-attitude: b = -.469, SE = .185, p = .011; attitude-ID: b = -.079, SE = .026, p = .002). These models are presented in Figures 41 (CLPM) and 42 (RI-CLPM). Thus, although at the between-person level Black respondents who identified more strongly as Black appeared more likely to support judicial discretion to depart from mandatory minimum sentences, the RI-CLPM results suggest that at the within-person level, an increase in identification as Black might predict a decrease in support for discretion to depart from mandatory minimum sentences, and vice versa.

a.



b.

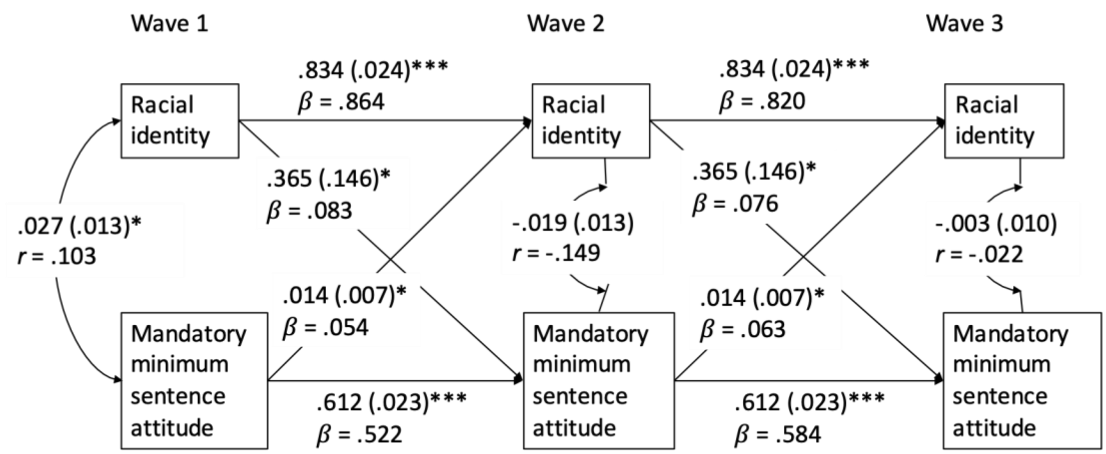


Figure 41. Study 2 CLPM for Black respondents' racial identity and support for judicial discretion to depart from mandatory minimum sentences, with the mandatory minimum sentence item treated as continuous, with no stationarity constraints (a), and with the mandatory minimum sentence item treated as categorical, with stationarity constraints on lagged and cross-lagged coefficients (b). Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

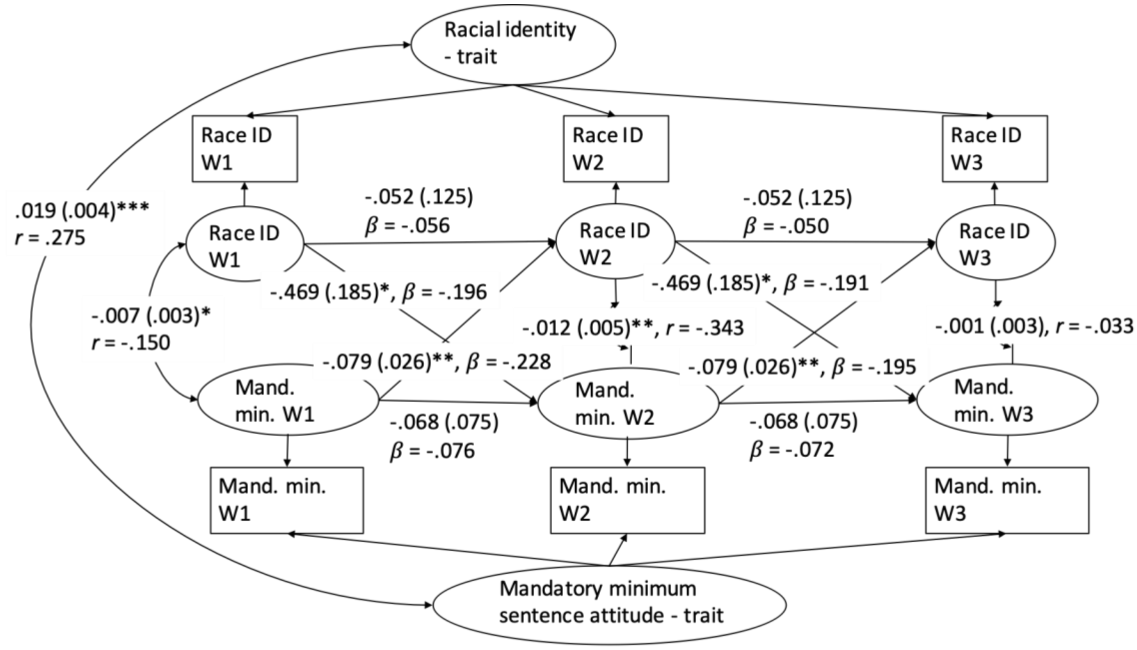
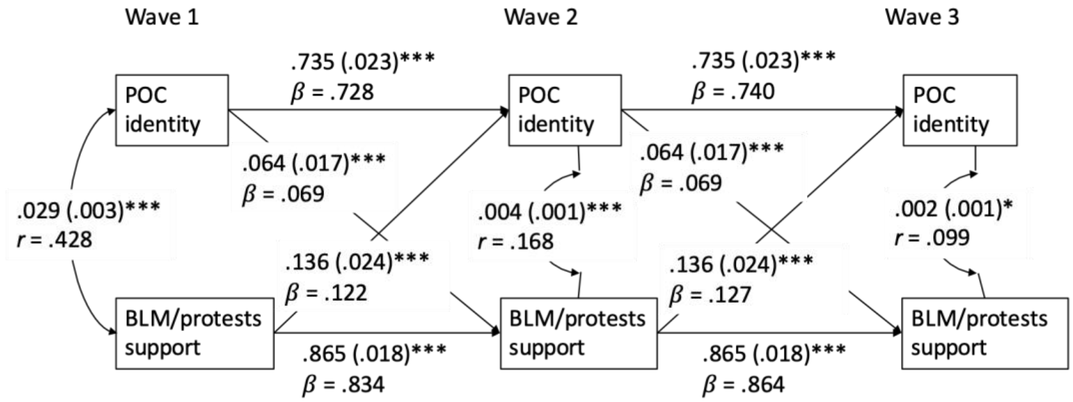


Figure 42. Study 2 RI-CLPM for Black respondents' racial identity and support for judicial discretion to depart from mandatory minimum sentences, with stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Unexpectedly, POC identity was also significantly positively associated with criminal justice reform attitudes among Black respondents. For the BLM/protest item, the pattern of effects with POC identity was similar to that for racial identity: POC identity also had a significant positive trait level covariance with BLM/protest support ($c = .030$, $SE = .003$, $p < .001$) in the RI-CLPM (with stationarity). Cross-lagged effects were significant and positive in both directions in both the CLPM (ID-attitude: $b = .064$, $SE =$

.017, p < .001; attitude-ID: b = .136, SE = .024, p < .001) and the RI-CLPM (ID-attitude: b = .115, SE = .056, p = .039; attitude-ID: b = .260, SE = .106, p = .014) (both models with stationarity). (Results from these models are illustrated in Figure 43.) Setting the identity-attitude and attitude-identity cross-lagged coefficients to be equal significantly or marginally significantly reduced model fit for both the CLPM ($\chi^2_8 = 119.808, \chi^2_9 = 125.465, \Delta\chi^2_1 = 5.657, p = .017$) and the RI-CLPM ($\chi^2_5 = 5.345, \chi^2_6 = 8.737, \Delta\chi^2_1 = 3.392, p = .066$). For the mandatory minimum sentence item, the only significant effect was a positive trait-level covariance (c = .014, SE = .005, p = .002) in the RI-CLPM (with stationarity).

a.



b.

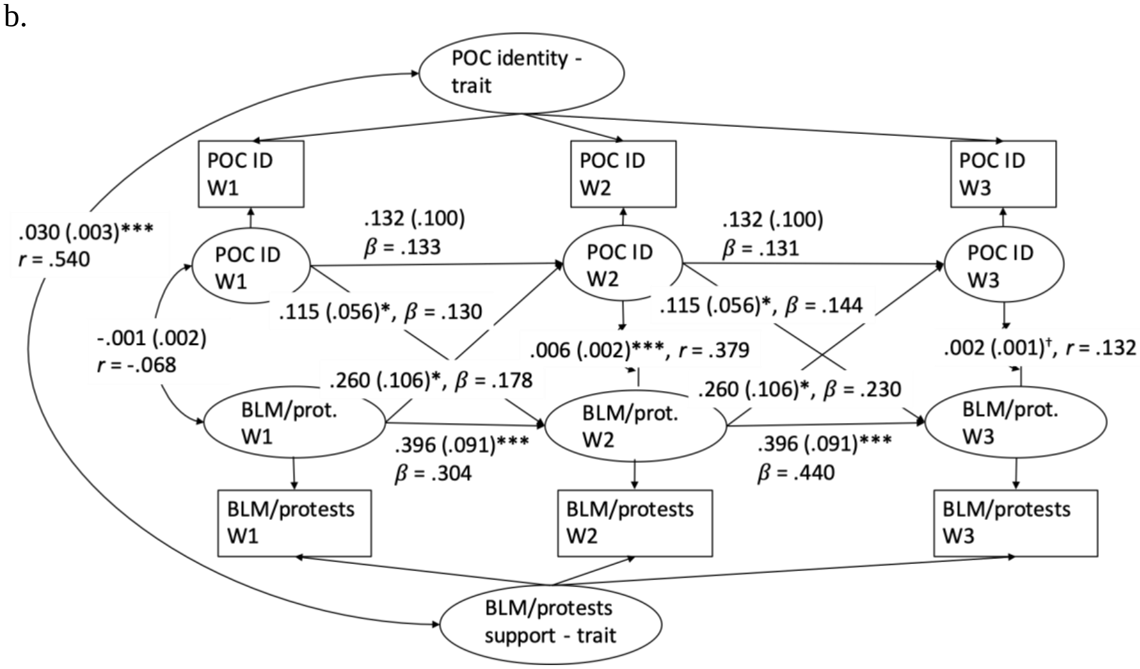


Figure 43. Study 2 CLPM (without covariates) (a) and RI-CLPM (b) for Black respondents' POC identity and support for Black Lives Matter and the George Floyd protests. Models include stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Evidence for Hypothesis 13 was again mixed. Black respondents' identification as American was not significantly related to their attitudes toward Black Lives Matter and the George Floyd protests. On the other hand, American identity did show a significant negative trait-level covariance with support for judicial discretion to give sentences below the mandatory minimum (c = -.009, SE = .004, p = .032, without stationarity). Without stationarity, which significantly worsened model fit when the mandatory minimum sentence variable was treated as continuous, the CLPM showed a negative attitude-identity effect from Wave 1 to Wave 2 (continuous variable model: b = -.043, SE = .017, p = .012; categorical variable model: b = -.039, SE = .013, p = .002) but a negative identity-attitude effect from Wave 2 to Wave 3 (continuous variable model: b = -.104, SE = .060, p = .083; categorical variable model: b = -.486, SE = .219, p = .026). With stationarity, the model treating the mandatory minimum sentence variable as categorical showed marginally significant negative cross-lagged effects in both directions (ID-attitude: b = -.216, SE = .127, p = .090; attitude-ID: b = -.012, SE = .007, p = .095). (The continuous variable CLPM model without stationarity and categorical variable CLPM with stationarity are presented in Figure 44.) But no significant cross-lagged effects appeared in the RI-CLPM, suggesting that, among African Americans, to the extent that higher American identity predicts decreased support for departures from mandatory minimum sentences, it does so primarily at the between-person level.

a.

b.

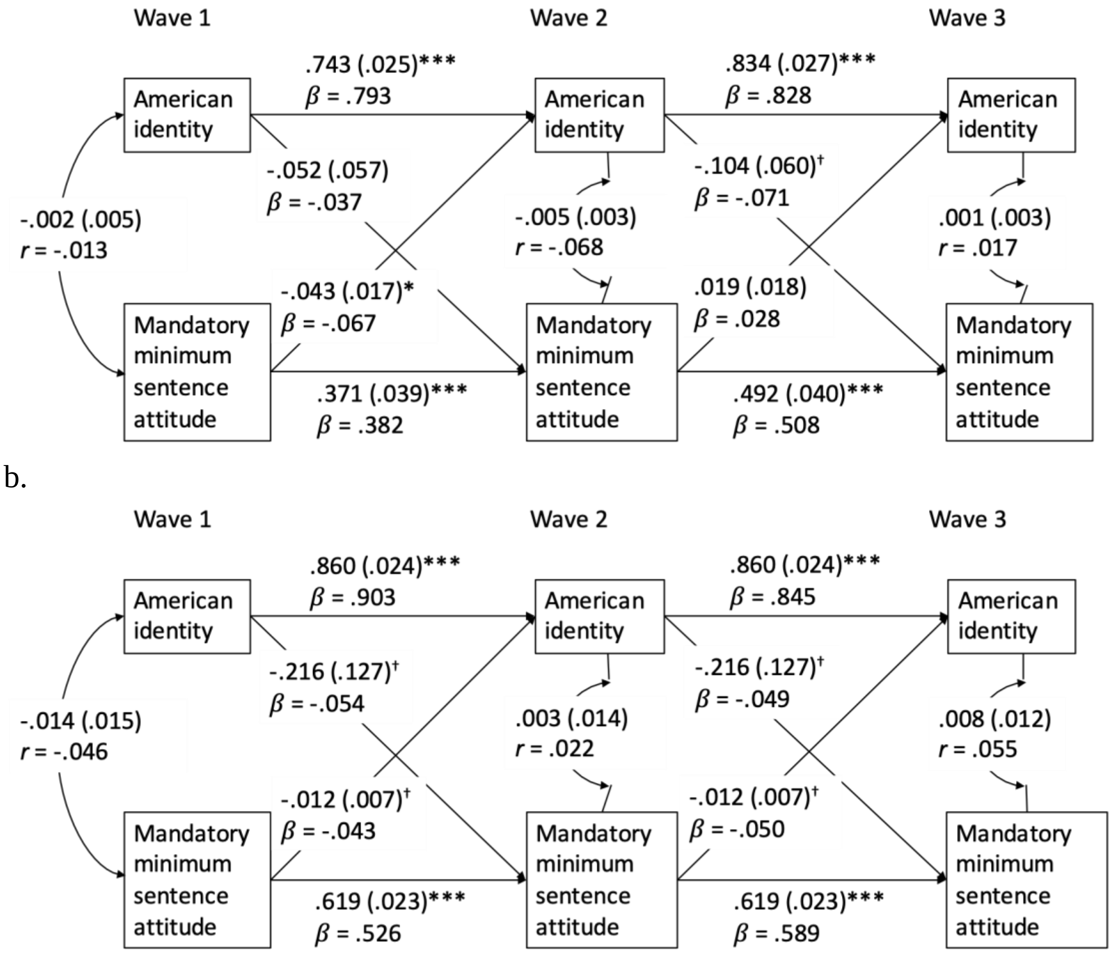


Figure 44. Study 2 CLPM for Black respondents' American identity and support for judicial discretion to depart from mandatory minimum sentences, treating the mandatory minimum sentence variable as continuous, with no stationarity constraints (a), and treating the mandatory minimum sentence variable as categorical, with stationarity constraints (b). Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Latino respondents. Fit statistics are presented in Tables 39 and 40. Again, CLPM models for the BLM/protests composite variable met the fit criteria for SRMR (.012-.073) but did not meet the criteria for RMSEA (.159-.295). CFI met or nearly met the fit criterion in the racial identity (CFI = .932-.958) and American identity (CFI = .923-.945, except no covariates + stationarity, CFI = .905) models but not in the POC identity model (CFI = .892-.931). Models treating the mandatory minimum sentence model as continuous met the fit criterion for SRMR (.019-.075), and the racial identity models met the criterion for CFI (.964-.977), as did the American identity model with covariates and without stationarity (CFI = .950); but the remaining models did not meet criterion for CFI (.844-.942), and none of the models met the criterion for RMSEA (.080-.211). Models treating this variable as categorical met or nearly met the criterion for CFI (non-robust CFI = .993-1.000; robust CFI = .930-.970), met the criterion for RMSEA with the non-robust statistic (RMSEA = .000-.043) but not consistently with the robust statistic (RMSEA = .056-.118), and met or nearly met the criterion for SRMR only when covariates were included (with covariates: SRMR = .067-.081; without covariates: SRMR = .153-.165). Stationarity significantly worsened CLPM model fit in the BLM/protest models with racial identity without covariates ($\chi^2_4 = 65.556, \chi^2_8 = 75.511, \Delta\chi^2_4 = 9.955, p = .041$), POC identity (without covariates: $\chi^2_4 = 98.933, \chi^2_8 = 113.801, \Delta\chi^2_4 = 14.868, p = .005$; with covariates: $\chi^2_4 = 92.768, \chi^2_8 = 101.054, \Delta\chi^2_4 = 8.286, p = .082$), and American identity (without covariates: $\chi^2_4 = 87.068, \chi^2_8 = 110.606, \Delta\chi^2_4 = 23.538, p < .001$; with covariates: $\chi^2_4 = 83.205, \chi^2_8 = 99.086, \Delta\chi^2_4 = 15.881, p = .003$), as well as the models with American identity and the mandatory minimum variable treated as continuous (without covariates: $\chi^2_4 = 40.356, \chi^2_8 =$

$52.891, \Delta\chi^2_4 = 12.535, p = .014$; with covariates: $\chi^2_4 = 41.072, \chi^2_8 = 50.384, \Delta\chi^2_4 = 9.312, p = .054$).

Table 39

Study 2 Panel Model Fit Statistics: Criminal Justice Attitudes (BLM/Protests), Latino Respondents

	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
Racial ID					
CLPM no covariates	.938	.238	.024	65.556 (4)***	
CLPM no cov w/ stationarity	.932	.176	.047	75.511 (8)***	9.955 (4)*
CLPM w/ covariates	.958	.224	.012	58.473 (4)***	
CLPM w/ cov w/ stationarity	.958	.159	.018	63.284 (8)***	4.811 (4)
RI-CLPM	1.000	.000	.001	0.009 (1)	65.547 (3)***
RI-CLPM w/ stationarity	1.000	.000	.017	2.270 (5)	2.261 (4)
POC ID					
CLPM no covariates	.903	.295	.050	98.933 (4)***	
CLPM no cov w/ stationarity	.892	.221	.073	113.801 (8)***	14.868 (4)**
CLPM w/ covariates	.931	.286	.026	92.768 (4)***	
CLPM w/ cov w/ stationarity	.928	.207	.032	101.054 (8)***	8.286 (4)†
RI-CLPM	.998	.093	.027	3.371 (1)†	95.562 (3)***
RI-CLPM w/ stationarity	1.000	.000	.036	4.688 (5)	1.317 (4)
American ID					
CLPM no covariates	.923	.276	.027	87.068 (4)***	
CLPM no cov w/ stationarity	.905	.217	.056	110.606 (8)***	23.538 (4)***
CLPM w/ covariates	.945	.270	.015	83.205 (4)***	
CLPM w/ cov w/ stationarity	.937	.205	.023	99.086 (8)***	15.881 (4)**
RI-CLPM	.999	.047	.013	1.606 (1)	85.462 (3)***
RI-CLPM w/ stationarity	1.000	.000	.016	2.555 (5)	0.949 (4)

Note: N = 272 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table 40

Study 2 Panel Model Fit Statistics: Criminal Justice Attitudes (Mandatory Minimum Sentence), Latino Respondents

	CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
Racial ID, continuous DV					
CLPM no covariates	.964	.115	.040	18.288 (4)**	
CLPM no cov w/ stationarity	.966	.080	.051	21.848 (8)**	3.560 (4)
CLPM w/ covariates	.977	.113	.019	17.884 (4)**	
CLPM w/ cov w/ stationarity	.976	.081	.024	22.207 (8)**	4.323 (4)
RI-CLPM	1.000	.000	.013	0.464 (1)	17.824 (3)***
RI-CLPM w/ stationarity	1.000	.000	.023	1.910 (5)	1.446 (4)
Racial ID, categorical DV					
CLPM no covariates	.996/.946	.037/.105	.155	5.450 (4)	
CLPM no cov w/ stationarity	1.000/.970	.000/.056	.153	7.766 (8)	2.316 (4)
CLPM w/ covariates	.999/.951	.016/.119	.079	4.295 (4)	
CLPM w/ cov w/ stationarity	1.000/.963	.005/.073	.067	8.050 (8)	3.755 (4)
POC ID					
CLPM no covariates	.853	.211	.059	52.532 (4)***	
CLPM no cov w/ stationarity	.844	.154	.075	59.731 (8)***	7.199 (4)
CLPM w/ covariates	.914	.211	.030	52.377 (4)***	
CLPM w/ cov w/ stationarity	.912	.151	.037	57.402 (8)***	5.025 (4)
RI-CLPM	1.000	.000	.014	0.550 (1)	51.982 (3)***
RI-CLPM w/ stationarity	.995	.036	.046	6.784 (5)	6.234 (4)
POC ID, categorical DV					
CLPM no covariates	.993/.930	.043/.105	.162	5.988 (4)	

CLPM no cov w/ stationarity	.994/.941	.028/.068	.165	9.757 (8)	3.769 (4)
CLPM w/ covariates	.998/.949	.027/.118	.081	4.778 (4)	
CLPM w/ cov w/ stationarity	1.000/.956	.008/.078	.071	8.135 (8)	3.357 (4)
American ID					
CLPM no covariates	.923	.183	.041	40.356 (4)***	
CLPM no cov w/ stationarity	.905	.144	.064	52.891 (8)***	12.535 (4)*
CLPM w/ covariates	.950	.185	.022	41.072 (4)***	
CLPM w/ cov w/ stationarity	.942	.140	.027	50.384 (8)***	9.312 (4)†
RI-CLPM	1.000	.000	.001	0.003 (1)	40.353 (3)***
RI-CLPM w/ stationarity	1.000	.000	.033	4.547 (5)	4.544 (4)
American ID, categorical DV					
CLPM no covariates	1.000/.956	.000/.091	.153	3.760 (4)	
CLPM no cov w/ stationarity	.999/.961	.009/.060	.146	8.192 (8)	4.432 (4)
CLPM w/ covariates	1.000/.963	.010/.110	.073	4.099 (4)	
CLPM w/ cov w/ stationarity	1.000/.962	.000/.079	.062	7.180 (8)	3.081 (4)

Note: N = 272 for all models.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

RI-CLPM significantly improved model fit over CLPM for all identity-criminal justice attitude combinations, and fit statistics indicated good model fit for all RI-CLPM models except POC identity and the BLM/protests variable without stationarity, which failed to meet the RMSEA criterion (RMSEA = .093). Again, however, the relatively small sample size of Latino respondents in this study cautions against interpreting cross-lagged effects in the RI-CLPM. Furthermore, although stationarity did not significantly affect RI-CLPM model fit, the RI-CLPM models with stationarity for the BLM/protests variable included a negative residual variance estimate for the Wave 2 attitude variable. Thus, RI-CLPM coefficients reported below are from the BLM/protest models without stationarity and the mandatory minimum sentence models with stationarity.

Evidence for Hypothesis 20 was mixed. Consistent with the hypothesis, POC identity had a significant positive trait-level covariance with attitudes toward Black Lives Matter and the George Floyd protests (c = .046, SE = .008, p < .001) in the RI-CLPM (without stationarity). Cross-lagged coefficients in the CLPM (again, without stationarity) were positive, though they suggested different directions of effects across time lags: Support for BLM and the protests in Wave 1 predicted POC identity in Wave 2 (b = .116, SE = .057, p = .043), but POC identity in Wave 2 predicted support for BLM and the protests in Wave 3 (b = .081, SE = .031, p = .009) (Figure 45). No significant cross-lagged effects appeared in the RI-CLPM, however. And POC identity did not appear to be significantly associated with Latino respondents' attitudes toward mandatory minimum sentences.

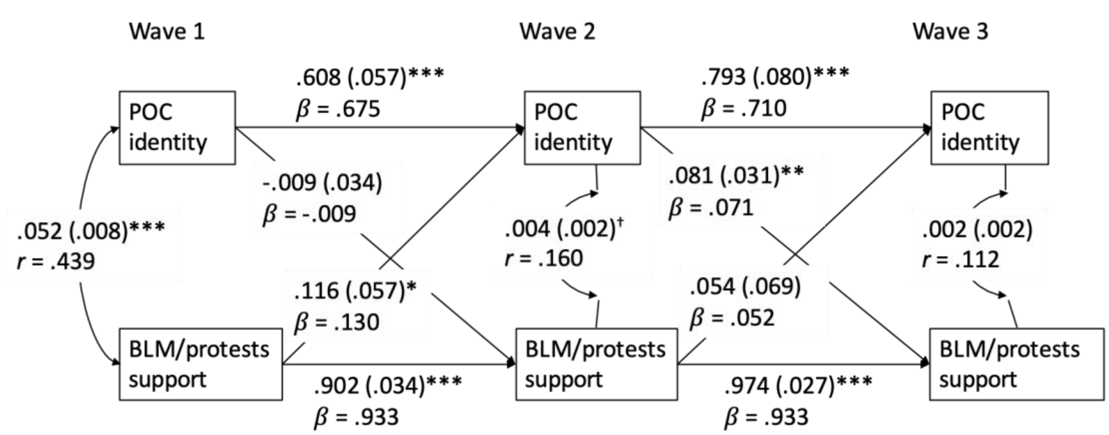
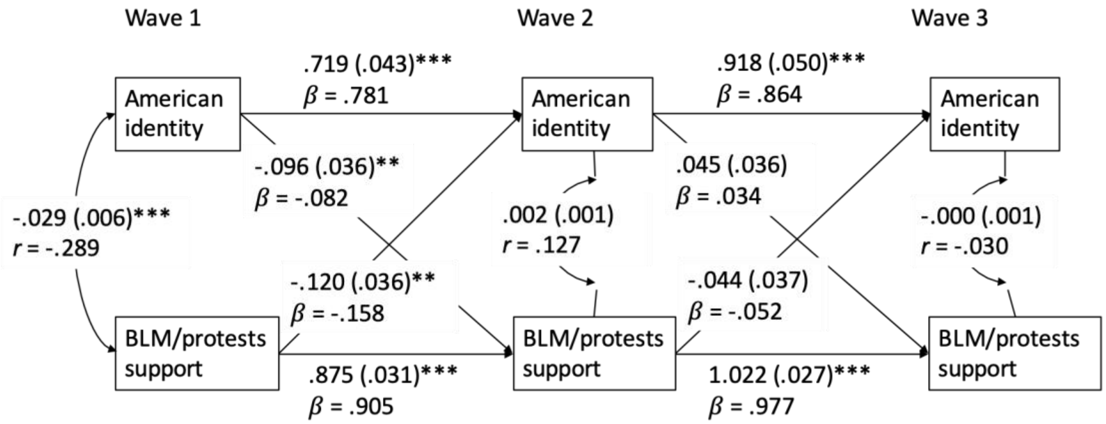


Figure 45. Study 2 CLPM for Latino respondents' POC identity and support for Black Lives Matter and the George Floyd protests, without covariates and with no stationarity constraints. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Consistent with Hypothesis 13, American identity had a significant negative trait-level covariance with attitudes toward both BLM/protests ($c = -.033$, $SE = .006$, $p < .001$, without stationarity) and departures from mandatory minimum sentences ($c = -.020$, $SE = .008$, $p = .012$, with stationarity). CLPM (without stationarity) showed significant negative cross-lagged effects from American identity to support for BLM and the protests and vice versa, but only from Wave 1 to Wave 2 (ID-attitude: $b = -.096$, $SE = .036$, $p = .008$; attitude-ID: $b = -.120$, $SE = .036$, $p = .001$). CLPM (with stationarity) with the mandatory minimum sentence variable treated as categorical showed a significant negative cross-lagged effect from American identity to support for departures from mandatory minimum sentences ($b = -.568$, $SE = .277$, $p = .040$), though this effect appeared only inconsistently in the models that treat the mandatory minimum sentence variable as continuous. (The CLPM models with the BLM/protests variable and with the categorical mandatory minimum sentence variable are presented in Figure 46.) No significant cross-lagged effects appeared in the RI-CLPM for either criminal justice reform variable. Thus, among Latino respondents, higher American identity appears to predict decreased support for criminal justice reform primarily at the between-person level.

a.



b.

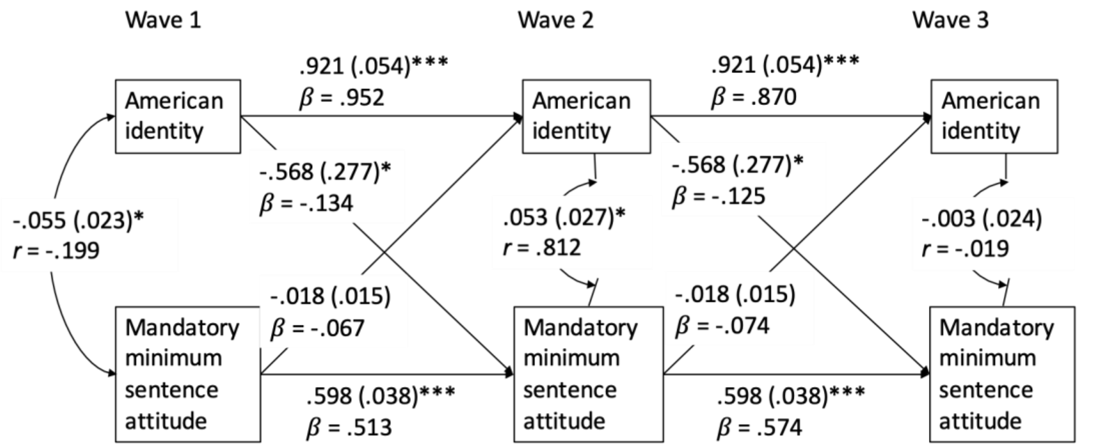


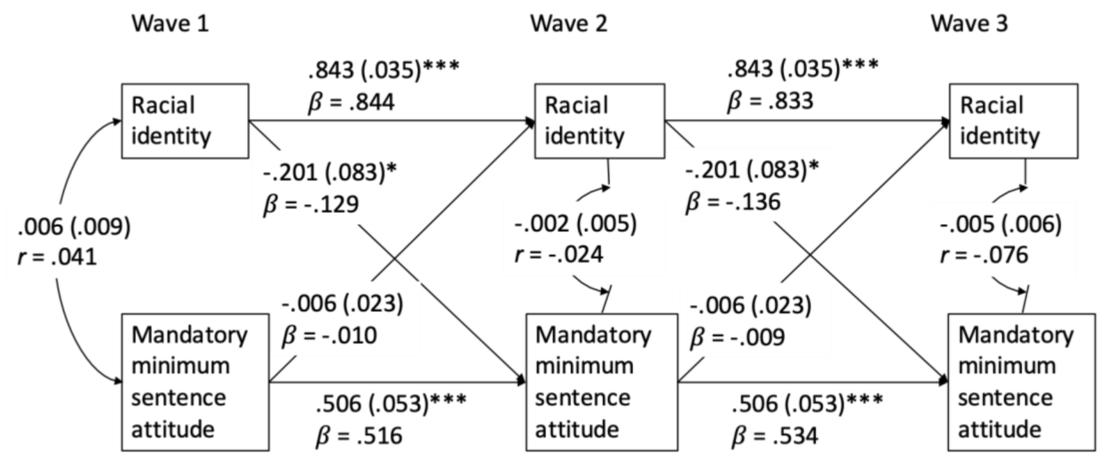
Figure 46. Study 2 CLPM for Latino respondents' American identity and support for Black Lives Matter and the George Floyd Protests, with no stationarity constraints (a), and support for judicial discretion to depart from mandatory minimum sentences (treated as categorical), with stationarity constraints (b). Models do not include covariates. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

Like POC identity, racial identity had a significant positive trait-level covariance (in the RI-CLPM without stationarity) with BLM/protest attitudes ($c = .020$, $SE = .006$, $p = .002$), though I predicted this association only for POC identity. But consistent with expectations, none of the cross-lagged effects with racial identity were significant in either the CLPM or the RI-CLPM.

On the other hand, racial identity had unexpected *negative* cross-lagged effects on support for judicial discretion to impose shorter sentences than the mandatory minimum. This effect is significant in the CLPM treating the mandatory minimum sentence variable as continuous ($b = -.201$, $SE = .083$, $p = .015$), marginally significant in the CLPM treating this variable as categorical ($b = -.472$, $SE = .261$, $p = .070$), and significant in the RI-CLPM ($b = -.810$, $SE = .297$, $p = .006$).[2] CLPM results (with stationarity) are presented in Figure 47; RI-CLPM results (with stationarity) are presented in Figure 48. Thus, it appears that not only does higher racial identification not increase Latino Americans' support for reducing the impact of mandatory minimum sentences, but it might in fact decrease their support for this aspect of criminal justice reform.

[2] Coefficients are from the models with stationarity.

a.



b.

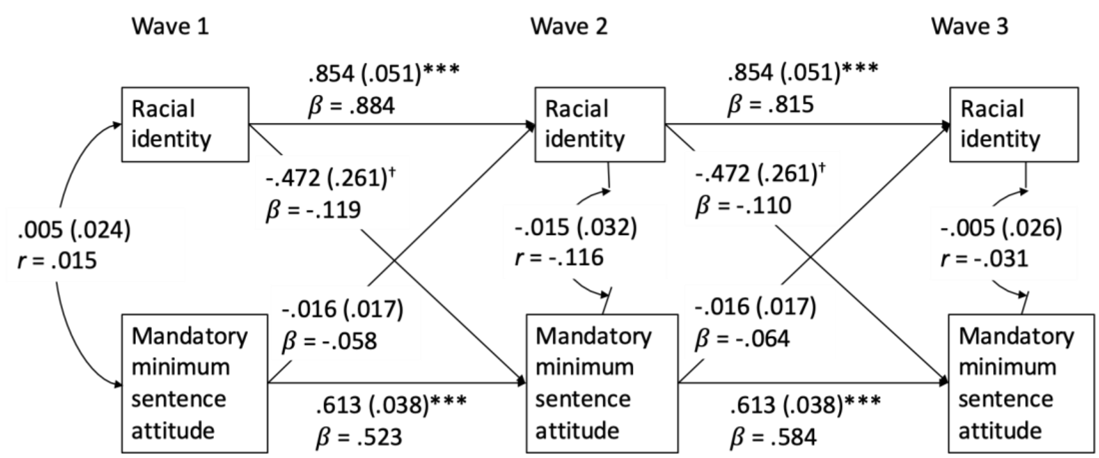


Figure 47. Study 2 CLPM for Latino respondents' racial identity and support for judicial discretion to depart from mandatory minimum sentences, treating the mandatory minimum sentence variable as continuous (a) and treating the mandatory minimum sentence as categorical (b). Models include stationarity constraints on lagged and cross-lagged coefficients. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** *p* < .001, ** *p* < .01, * *p* < .05, † *p* < .10 (marginally significant).

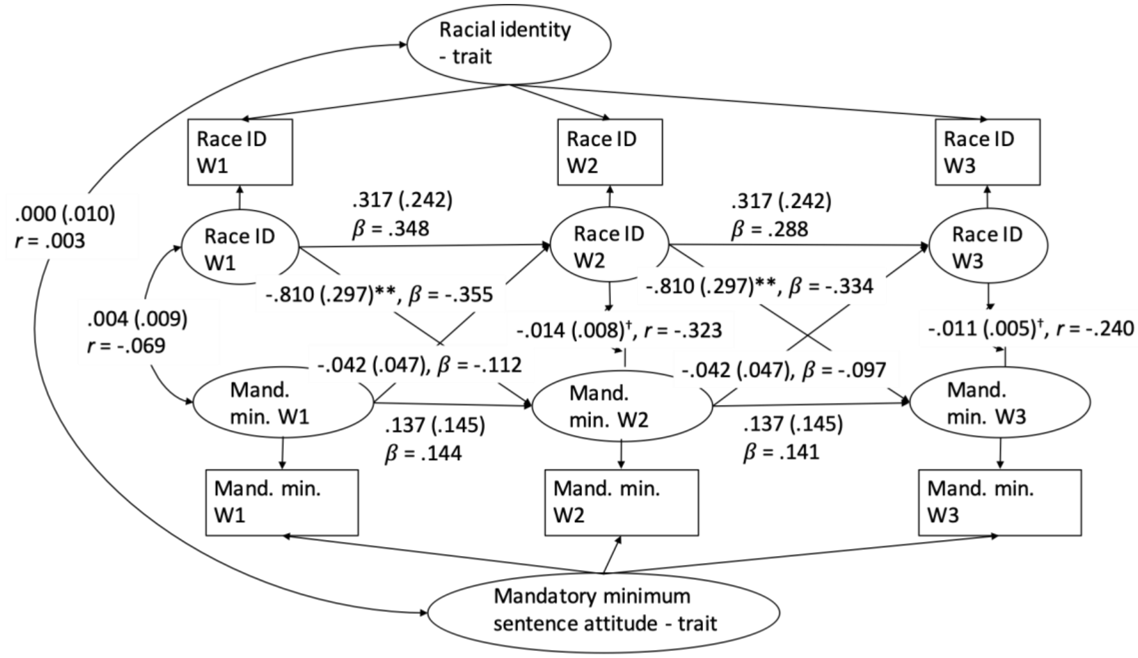


Figure 48. Study 2 RI-CLPM for Latino respondents' racial identity and support for judicial discretion to depart from mandatory minimum sentences, with stationarity constraints on lagged and cross-lagged effects. Unstandardized coefficients with standard errors (in parentheses) and standardized coefficients are shown. Statistical significance is indicated as follows: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$ (marginally significant).

4. Identity-Policy Attitude Indirect Effects

I examined whether linked fate (the only potential mediator measured in Study 2) mediated the effects of each identity on each policy attitude item. As discussed in Chapter 1, I expected linked fate to connect racial and POC identities, but not American identity, with policy attitudes (Hypotheses 21-24). Additionally, because linked fate and group consciousness might be more closely related for African Americans than for other racial groups, linked fate could potentially pick up the effects of other, unmeasured, group consciousness variables among Black respondents but not Latino respondents; thus, indirect effects through linked fate seemed more likely to appear for Black respondents than for Latino respondents, and Hypotheses 23 and 24 (addressing mediation effects for Latino respondents) were tentative.

As with the Study 1 data, I fit full models (with lagged or cross-lagged paths from each variable to every variable in the next wave and covariances or residual covariances among all three variables within each wave), models with stationarity across time lags, and directional models (with only forward structural paths). For immigration attitudes, CFI varied greatly for Latino respondents (.855-.961) but was generally just below acceptable for Black respondents (.909-.942), SRMR generally indicated good fit for both groups (SRMR ≤ .079), and RMSEA indicated poor fit except for Latinos on the ending criminal penalties item (RMSEA = .065-.099; Latino respondents, all other models RMSEA = .097-.192; Black respondents RMSEA = .096-.189). For criminal justice reform, continuous variable models had a similar pattern of fit statistics (Black respondents: CFI = .906-.957, RMSEA = .109-184, SRMR = .028-.061; Latino respondents: CFI = .875-.956, RMSEA = .071-.201, SRMR = .029-.092). In contrast to Study 1, models with stationarity and/or directionality typically did not fit significantly worse than the full models. (Fit statistics are presented in Tables 41-44.) Where one model did not significantly worsen fit but the other did, I report results from the model that did not significantly affect fit; where neither model significantly worsened fit, I report results from the model with better fit statistics (i.e., CFI, RMSEA, and SRMR), which was generally the model with stationarity.

Table 41

Study 2 Mediation Model Fit Statistics: Immigration Attitudes (Black Respondents)

		CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Racial ID						
Number of immigrants	*full*	.919	.185	.042	211.419 (9)***	
	stationarity	.919	.130	.045	219.030 (18)***	7.611 (9)
	directional	.909	.152	.062	242.544 (15)	31.125 (6)***
Ending criminal penalties	*full*	.924	.154	.043	149.597 (9)***	
	stationarity	.924	.109	.046	159.756 (18)***	10.159 (9)
	directional	.918	.124	.050	167.909 (15)***	18.312 (6)**
IV: POC ID						
Number of immigrants	*full*	.933	.167	.039	174.808 (9)***	
	stationarity	.931	.120	.043	187.552 (18)***	12.744 (9)
	directional	.925	.137	.059	200.334 (15)***	25.526 (6)***
Ending criminal penalties	*full*	.942	.134	.040	115.554 (9)***	
	stationarity	.941	.096	.043	126.029 (18)***	10.475 (9)
	directional	.938	.107	.046	128.798 (15)***	13.244 (6)*
IV: American ID						
Number of immigrants	*full*	.914	.189	.042	219.927 (9)***	
	stationarity	.913	.134	.046	231.186 (18)***	11.259 (9)
	directional	.910	.150	.053	237.240 (15)***	17.313 (6)**
Ending criminal penalties	*full*	.917	.162	.042	163.646 (9)***	
	stationarity	.913	.116	.047	178.407 (18)***	14.761 (9)†
	directional	.915	.126	.044	172.252 (15)***	8.606 (6)

Table 42

Study 2 Mediation Model Fit Statistics: Immigration Attitudes (Latino Respondents)

		CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Racial ID						
Number of immigrants	*full*	.922	.158	.044	70.434 (9)***	
	stationarity	.919	.114	.053	81.374 (18)***	10.940 (9)
	directional	.916	.127	.062	80.886 (15)***	10.452 (6)
Ending criminal penalties	*full*	.954	.099	.041	33.110 (9)***	
	stationarity	.961	.065	.051	38.536 (18)**	5.426 (9)
	directional	.958	.073	.051	36.953 (15)**	3.843 (6)
IV: POC ID						
Number of immigrants	*full*	.883	.192	.055	98.938 (9)***	
	stationarity	.876	.140	.064	113.746 (18)***	14.808 (9)†
	directional	.876	.153	.079	110.502 (15)***	11.564 (6)†
Ending criminal penalties	*full*	.861	.171	.056	80.656 (9)***	
	stationarity	.855	.124	.067	92.775 (18)***	12.119 (9)
	directional	.864	.131	.067	85.205 (15)***	4.549 (6)
IV: American ID						
Number of immigrants	*full*	.914	.173	.044	82.083 (9)***	
	stationarity	.889	.139	.076	112.582 (18)***	30.499 (9)***
	directional	.902	.143	.074	98.516 (15)***	16.433 (6)*
Ending criminal penalties	*full*	.938	.120	.043	44.103 (9)***	
	stationarity	.907	.103	.071	70.352 (18)***	26.249 (9)**
	directional	.932	.097	.056	53.410 (15)***	9.307 (6)

Table 43

Study 2 Mediation Model Fit Statistics: Criminal Justice Attitudes (Black Respondents)

		CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Racial ID						
BLM/protests	*full*	.949	.174	.030	188.828 (9)***	
	stationarity	.949	.123	.034	198.338 (18)***	9.510 (9)
	directional	.935	.153	.073	246.529 (15)***	57.701 (6)***
Mandatory minimum sentence (continuous)	*full*	.914	.172	.049	183.346 (9)***	
	stationarity	.911	.123	.053	198.538 (18)***	15.192 (9)†
	directional	.907	.138	.061	203.537 (15)***	20.191 (6)**
Mandatory minimum sentence (categorical)	*full*	.984/.848	.064/.135	.108	32.856 (9)***	
	stationarity	.984/.907	.045/.075	.108	41.946 (18)**	9.090 (9)
	directional	.982/.848	.052/.104	.111	41.913 (15)***	9.057 (6)
IV: POC ID						
BLM/protests	*full*	.957	.160	.028	159.946 (9)***	
	stationarity	.956	.114	.030	171.940 (18)***	11.994 (9)
	directional	.943	.142	.070	214.682 (15)***	54.736 (6)***
Mandatory minimum sentence (continuous)	*full*	.933	.151	.047	143.649 (9)***	
	stationarity	.929	.109	.050	159.252 (18)***	15.603 (9)†
	directional	.928	.121	.056	158.921 (15)***	15.272 (6)*
Mandatory minimum sentence (categorical)	*full*	.985/.852	.061/.132	.110	31.218 (9)***	
	stationarity	.985/.910	.043/.073	.108	39.639 (18)**	8.421 (9)
	directional	.984/.862	.049/.098	.111	38.574 (15)**	7.356 (6)
IV: American ID						
BLM/protests	*full*	.942	.184	.031	208.943 (9)***	
	stationarity	.942	.130	.034	217.324 (18)***	8.381 (9)
	directional	.933	.153	.059	244.950 (15)***	36.007 (6)***

Mandatory minimum sentence (continuous)	*full*	.911	.174	.047	187.881 (9)***	
	stationarity	.906	.126	.053	207.081 (18)***	19.200 (9)*
	directional	.908	.137	.053	200.799 (15)	12.918 (6)*
Mandatory minimum sentence (categorical)	*full*	.981/.851	.060/.125	.107	30.088 (9)***	
	stationarity	.978/.888	.045/.077	.107	42.432 (18)**	12.344 (9)
	directional	.977/.846	.051/.099	.111	40.811 (15)***	10.723 (6)[†]

Table 44

Study 2 Mediation Model Fit Statistics: Criminal Justice Attitudes (Latino Respondents)

		CFI	RMSEA	SRMR	χ^2 (df)	$\Delta\chi^2$ (df)
IV: Racial ID						
BLM/protests	*full*	.946	.163	.029	73.931 (9)***	
	stationarity	.942	.119	.045	87.913 (18)***	13.982 (9)
	directional	.937	.136	.080	90.790 (15)***	16.859 (6)**
Mandatory minimum sentence (continuous)	*full*	.954	.103	.043	34.841 (9)***	
	stationarity	.956	.071	.055	42.767 (18)**	7.926 (9)
	directional	.956	.078	.056	39.734 (15)***	4.893 (6)
Mandatory minimum sentence (categorical)	*full*	1.000/.932	.000/.081	.109	5.294 (9)	
	stationarity	1.000/.984	.000/.028	.104	9.896 (18)	4.602 (9)
	directional	1.000/.957	.000/.050	.114	10.388 (15)	5.094 (6)
IV: POC ID						
BLM/protests	*full*	.918	.201	.043	108.330 (9)***	
	stationarity	.907	.152	.062	130.828 (18)***	22.498 (9)**
	directional	.913	.161	.080	120.957 (15)***	12.627 (6)*

Mandatory minimum sentence (continuous)	*full*	.890	.156	.055	68.857 (9)***	
	stationarity	.875	.118	.070	85.743 (18)***	16.886 (9)†
	directional	.888	.122	.070	75.896 (15)***	7.039 (6)
Mandatory minimum sentence (categorical)	*full*	1.000/.912	.000/.088	.116	6.572 (9)	
	stationarity	1.000/.966	.000/.039	.113	12.111 (18)	5.539 (9)
	directional	1.000/.945	.000/.054	.120	10.652 (15)	4.080 (6)
IV: American ID						
BLM/protests	*full*	.936	.183	.030	90.762 (9)***	
	stationarity	.914	.149	.059	127.221 (18)***	36.459 (9)***
	directional	.918	.160	.092	119.965 (15)***	29.203 (6)***
Mandatory minimum sentence (continuous)	*full*	.930	.131	.044	51.139 (9)***	
	stationarity	.898	.112	.073	79.564 (18)***	28.425 (9)***
	directional	.924	.106	.059	60.756 (15)***	9.617 (6)
Mandatory minimum sentence (categorical)	*full*	1.000/.941	.000/.073	.109	5.060 (9)	
	stationarity	1.000/.954	.000/.046	.107	13.437 (18)	8.377 (9)
	directional	1.000/.931	.000/.061	.116	11.803 (15)	6.743 (6)

Indirect and total effects were defined and estimated as they were in Study 1. In this study, indirect effects were marginally significant at best. Linked fate appeared to mediate the effect of racial identity on Black respondents' preference for allowing more immigrants into the U.S. (*ab* = .005, *SE* = .003, *p* = .083; 95% CI: [.000, .012])[3] and support for Black Lives Matter and the George Floyd protests (*ab* = .003, *SE* = .002, *p* = .071; 95% CI: [.000, .007]).[4] The total effect was also significant (and positive) for the latter (t = .074, *SE* = .035, *p* = .037; 95% CI: [.003, .141])[5] but not for the former. These two mediation models are presented in Figures 51 (number of immigrants) and 52 (BLM/protests). As can be seen, racial identity significantly predicted linked fate in both models (number of immigrants: *b* = .159, *SE* = .039, *p* < .001; BLM/protests: *b* = .088, *SE* = .043, *p* = .039). Linked fate, in turn, significantly predicted BLM/protest attitudes (*b* = .037, *SE* = .012, *p* = .003) but only marginally significantly predicted preference for number of immigrants (*b* = .034, *SE* = .018, *p* = .058).

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[3] Model with stationarity.
[4] Model with stationarity.
[5] Model with stationarity.

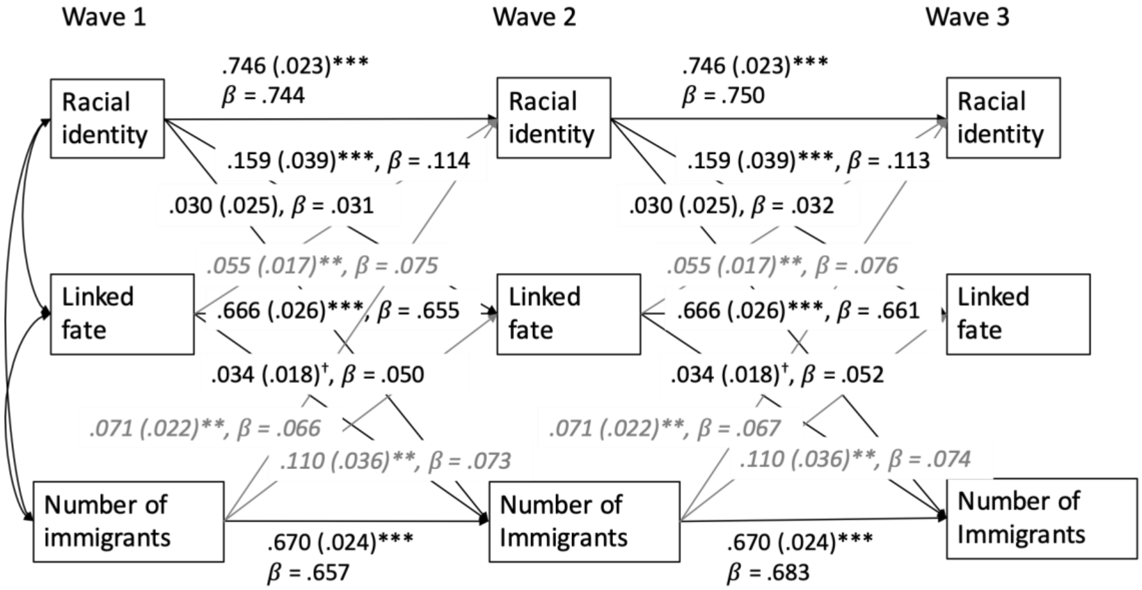

Figure 49. Study 2 longitudinal mediation model, with stationarity constraints, of the effect of Black respondents' racial identity on attitudes toward the number of immigrants who should be allowed into the U.S., via linked fate. Reverse effects are shown in gray and italics. Within-wave covariances are omitted for readability. Standard errors and confidence intervals for indirect and total effects were estimated using the se = "bootstrap" option in lavaan with the default number of bootstrap samples. Indirect effect *ab* = .005 (.003), *p* = .083, 95% CI: [.000, .012]. Total effect from Wave 1 racial identity to Wave 3 attitude (*xc* + *cy* + *ab*) = .047 (.037), *p* = .200, 95% CI: [-.024, .118].

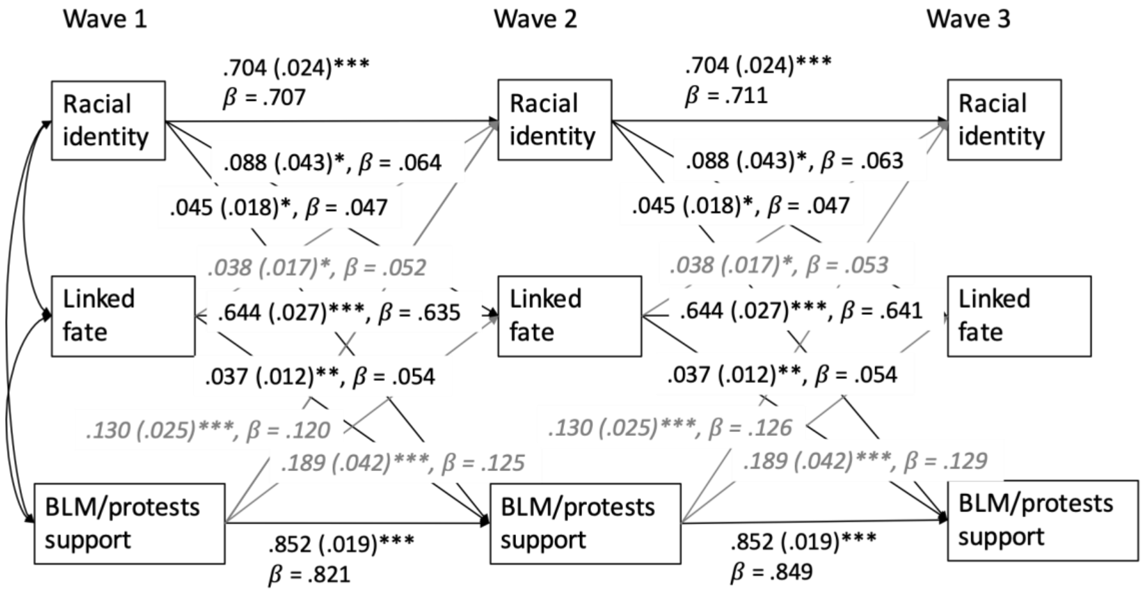

Figure 50. Study 2 longitudinal mediation model, with stationarity constraints, for Black respondents' racial identity and support for Black Lives Matter and the George Floyd protests, via linked fate. Reverse effects are shown in gray and italics. Within-wave covariances are omitted for readability. Indirect effect *ab* = .003 (.002), *p* = .071; 95% CI: [.000, .007]. Total effect from Wave 1 racial identity to Wave 3 attitude (*xc* + *cy* + *ab*) = .074 (.035), *p* = .037, 95% CI: [.003, .141].

A number of other total effects were significant in the mediation models. Similar to the CLPM, POC identity in the mediation models had a significant (positive) total effect on Black respondents' preference for allowing more immigrants (t = .086, *SE* = .039, *p* = .028; 95% CI: [.007, .158])[6] and Latino respondents' support for ending criminal penalties for immigration (t = .162, *SE* = .075, *p* = .030; 95% CI: [.005, .302]).[7]

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[6] Model with stationarity.
[7] Directional model.

American identity had a marginally significant (negative) total effect on Latino respondents' support for ending criminal penalties for immigration (t = -.165, *SE* = .099, *p* = .095; 95% CI: [-.376, .012]).[8] Black respondents' racial identity had a marginally significant total effect on support for discretion to depart from mandatory minimum sentences (continuous variable model: t = .106, *SE* = .061, *p* = .083; 95% CI: [-.021, .221]; categorical variable model: t = .401, *SE* = .224, *p* = .074; 95% CI: [-.056, .820]).[9] Again, however, Black respondents' POC identity (in addition to their racial identity) had a significant total effect on BLM/protest support (t = .083, *SE* = .032, *p* = .009; 95% CI: [.020, .146]),[10] and Latino respondents' racial identity had a marginally significant total effect on this variable (t = .071, *SE* = .037, *p* = .058; 95% CI: [-.002, .141])[11] while their POC identity did not. But as was the case in the CLPM, Latino respondents' racial identity had a marginally significant to significant *negative* total effect on support for discretion to depart from mandatory minimum sentences (continuous variable model: t = -.301, *SE* = .102, *p* = .003; 95% CI: [-.005, -.101]; categorical variable model: t = -.911, *SE* = .515, *p* = .077; 95% CI: [-2.246, -.178]).[12] American identity had a marginally significant to significant total effect on support for discretion on mandatory minimum sentences for Black respondents (continuous variable model: t = -.107, *SE* = .047, *p* = .023; 95% CI: [-.198, -.009]; categorical variable model: t = -.357, *SE* = .201, *p* = .076;

[8] Directional model.
[9] Both models with stationarity.
[10] Model with stationarity.
[11] Model with stationarity.
[12] Both models with stationarity.

95% CI: [-.760, .021])[13] and for Latino respondents when the mandatory minimum sentence variable was treated as categorical (t = -.825, *SE* = .387, *p* = .033; 95% CI: [-1.580, -.084]).[14]

Overall, the results of Study 2 provide limited support for linked fate as a mediator of the effects of racial or POC identity on Black (Hypotheses 21-22) or Latino (Hypotheses 23-24) respondents' policy attitudes.

C. Discussion

As was the case in Study 1, the results of Study 2 are consistent with most of my hypotheses at the trait level but do not consistently *support* the hypotheses, which are directional. The fact that I found mainly trait-level covariances could be due in part to high variable stability, as in Study 1. However, stability was not as high for at least the policy variables in Study 2 as it was in Study 1. Nonetheless, the pattern of significant trait-level covariances and inconsistent cross-lagged effects held across studies.

At the trait level, POC identity was associated with more positive attitudes toward other racial minority groups (who are included in this common ingroup identity) among both Black and Latino respondents, consistent with Hypothesis 2. However, cross-lagged effects were only significant in the CLPM for Black respondents between Wave 2 and Wave 3. Thus, Study 2 provides little evidence that POC identity predicts changes in attitudes toward other racial minorities and no evidence that changing POC identification can change Black or Latino individuals' attitudes toward other racial minorities.

[13] The model treating the mandatory minimum sentence variable as continuous is the full model. The model treating this variable as categorical is the model with stationarity.
[14] Model with stationarity.

For Black respondents, American identity was associated at the trait level with more positive attitudes toward both other racial minority groups and Whites (all of whom should in theory be included in this common ingroup identity), consistent with Hypothesis 1. Significant cross-lagged effects in the CLPM provide evidence that, at the between-person level, African Americans who identify more strongly as American tend to show improvements in their attitudes toward both other minorities and Whites. But a marginally significant negative cross-lagged effect in the RI-CLPM suggests that increases in American identity at the within-person level might have the opposite effect on attitudes toward other racial minorities. Thus, although individual differences in American identity do seem to predict changes in racial attitudes among African Americans, Study 2 does not support the idea that increasing individuals' identification as American would improve their attitudes toward other groups as predicted by the common ingroup identity model.

For Latino respondents, at the trait level, American identity was associated with more positive attitudes toward Whites but not associated with attitudes toward other racial minorities. Together with the stronger effects of American identity on attitudes toward Whites than on attitudes toward other minorities among Asian Americans in Study 1, this finding for Latino respondents suggests that Americanness might have some association with whiteness for members of some minority groups. However, positive cross-lagged effects from Wave 1 to Wave 2 in this study suggest that increases in American identity could possibly predict improvements in attitudes toward other minorities as well as Whites, at both the between-person and within-person levels,[15] though negative coefficients (albeit generally non-significant) from Wave 2 to Wave 3 caution against giving too much weight to the positive effects. Overall, Study 2 provides inconsistent evidence that American identity functions as a common ingroup identity in predicting Latino Americans' racial attitudes.

Consistent with Hypothesis 19 and the collective action literature, Black respondents' racial identity was associated at the trait level with more support for criminal justice reform, the policy area more closely tied to their own group. However, the pattern of cross-lagged effects provides mixed evidence at best: Support for Black Lives Matter and the George Floyd protests appears to predict African Americans' racial identification more than racial identification predicts support for BLM and the protests, and racial identification appears to predict more support for departures from mandatory minimum sentences at the between-person level (i.e., trait-level covariance in the RI-CLPM and to some extent, cross-lagged effects in the CLPM) but less support at the within-person level (i.e., cross-lagged effects in the RI-CLPM). At the same time, Black respondents' racial identity was also associated at the trait level with more liberal immigration attitudes (a policy area more closely tied to Latinos), and Latino respondents' racial identity was not significantly associated with their immigration

[15] At the within-person level, the cross-lagged effect of American identity on nonwhite FTs among Latino respondents despite the lack of trait-level covariance is consistent with the Study 1 finding of a positive cross-lagged effect of Asian respondents' American identity on nonwhite FTs despite the lack of trait-level covariance and between-person cross-lagged effects. However, if this is a true effect despite the low statistical power in this study, it is unclear how to interpret it in light of the inconsistency across time lags for Latino respondents and the inconsistency across racial attitude measures for Asian American respondents.

attitudes (in terms of trait-level covariances or cross-lagged effects in either the CLPM or RI-CLPM) but was associated with more positive attitudes toward Black Lives Matter and the George Floyd protests at the trait level. Thus, Study 2 does not show that racial identity either consistently or exclusively predicts own-group policy attitudes (Hypotheses 5, 17, & 18); the connection between racial identity and policy attitudes appears to be both broader and narrower than social identity-based collective action theories would predict.

POC identity also appears to relate to policy attitudes both more broadly and more narrowly than I predicted. I expected that identification as POC would primarily make other-group issues self-relevant and would thus primarily be associated with increases in support for other-group policies (Hypotheses 6, 19, & 20). Consistent with these expectations, POC identity was associated at the trait level with more liberal immigration attitudes among Black respondents and more positive attitudes toward Black Lives Matter and the George Floyd protests among Latino respondents. However, cross-lagged coefficients from POC identity to immigration attitudes were not significant for Black respondents, and Latino respondents' identification as POC appeared to predict support for BLM and the protests inconsistently and only in the CLPM. Thus, the evidence is mixed at best as to whether POC identity predicts support for other-group policies. Similar relationships between these policy items and racial identity further suggest that POC identity is not necessary to make these issues self-relevant. At the same time, POC identity, but not racial identity, was associated with Latino respondents' immigration attitudes, and results from the CLPM and RI-CLPM suggest that increases in Latinos' POC identification predict increases in support for ending criminal penalties for illegal immigration at both the between- and within-person levels. Additionally, POC identity was associated with support for discretion to depart from mandatory minimum sentences among Black respondents (though only at the trait level). These two findings, along with the fact that POC identity but not racial identity had cross-lagged effects on Asian Americans' immigration attitudes in Study 1, suggest that POC identity might play a role in attitudes toward own-group policies.

Consistent with the paradoxical effects literature, American identity was associated with less liberal immigration attitudes and less support for criminal justice reform at the trait level for Latino respondents (Hypothesis 13). Cross-lagged effects were inconsistent across models and time lags, however, and were only significant in the CLPM. For Black respondents, the trait-level covariances were significant for only one of the immigration items (ending criminal penalties) and one of the criminal justice items (mandatory minimum sentences). Cross-lagged effects of identity on attitude were only marginally significant and relied on the stationarity assumption for the immigration item and were inconsistent across waves and only present in the CLPM for the criminal justice item. That the trait-level covariances were negative and significant across the board for Latino respondents but not for Black respondents suggests that the association between this particular common ingroup identity and support for the racial status quo might be stronger for some racial minority groups than for others. And in theory, this association could make Latino Americans particularly susceptible to the paradoxical effects of identifying as American. But because of the inconsistent cross-lagged effects, especially in the RI-CLPM, this study does not demonstrate that these paradoxical effects actually occurred with either Black or Latino respondents.

A specific limitation of this study is the smaller sample size of Latino respondents (Wave 1 N = 272, Wave 2 N = 146, Wave 3 N = 120). This sample size is smaller than any of the potential sample sizes I used to estimate statistical power for RI-CLPM, and thus, the RI-CLPM models, especially without stationarity, are likely underpowered for detecting cross-lagged effects. As a result, one should be cautious in drawing any conclusions about the presence or absence of within-person effects among Latino respondents.

Another limitation is that the panel models in this study focus on one identity at a time without controlling for the other identities. In Study 1, correlations among the identities of interest were accounted for in the factor scores, which were generated from CFAs that included all three identities. The composite scores I used in this study do not account for these correlations. Not accounting for correlations among identities is most likely to have had an impact on the results for Black respondents, who had the highest racial identity-POC identity correlation out of the three respondent groups (r = .83-.88). And high correlations between these two identities could explain why the effects of racial and POC identities often appear to be similar (though this explanation does not provide insight into which identity is actually driving the effect).

Additionally, the negative cross-lagged effects of Latino respondents' racial identity on support for judicial discretion on mandatory minimum sentences raise questions about how respondents interpreted that item, especially because Latino respondents' racial identity predicted more positive attitudes on the other criminal justice variable. Were respondents reading judicial discretion to impose less harsh sentences as somehow unfair to Latino Americans? It is not readily apparent from the aggregate data what respondents' interpretations were or how those might have affected the relationships between the mandatory minimum sentence variable and POC and American identities.

Finally, the only potential mediator included in Study 2 was linked fate. Thus, Study 2 could not fully test the mechanisms of identity effects on policy attitudes suggested by the collective action, group consciousness, and paradoxical effects literatures. Although I did find marginally significant indirect effects of Black respondents' racial identity on one own-group policy item and one other-group policy item, these were two marginally significant effects across several combinations of identity and policy attitude and thus do not constitute strong evidence of a linked fate mechanism. I found no evidence that linked fate connects identity and policy attitudes for Latinos.

Overall, Study 2 provides evidence consistent with but not supporting the idea that POC and American identities serve the prejudice reduction function of a common ingroup identity (Hypotheses 1 & 2) for Black and Latino Americans. It provides evidence consistent with the idea that racial identity increases support for policies that benefit minority groups and some evidence (with Latino respondents and ending criminal penalties for immigration) supporting the idea that POC identity increases support for such policies. However, my distinction between own-group and other-group issues (i.e., the distinction between Hypothesis 5 and Hypothesis 6) was not supported, as racial identity was associated with some other-group issues and POC identity was associated with some own-group issues. What implications this lack of a distinction between own-group and other-group issues has for the group-identity-based self-relevance process described by van Zomeren et al. (2012) is potentially a topic for future research. Study 2 also provides evidence consistent with but not supporting the idea that American identity has a paradoxical effect of reducing support for policies that benefit racial minority groups (Hypotheses 7 & 13). And like Study 1, Study 2 provides little evidence for the proposed mechanisms behind identity effects on policy attitudes (Hypotheses 21-24).

Chapter 5: Discussion & Conclusions

Using two 3-wave panel studies, I explored 1) whether common ingroup identity has the same prejudice reduction effects on minority group members' attitudes toward other minority groups as have been found consistently for majority group members and 2) whether common ingroup identity has the same prejudice reduction and paradoxical effects on minority group members when it does and does not include the majority group. Through these studies, I attempted to bridge gaps between social psychology research on common ingroup identity, social and political psychology research on collective action, and political psychology research on racial identity and political attitudes.

A. Common Ingroup Identity and Racial Attitudes

First, I expected to replicate the finding that common ingroup identity reduces prejudice (Gaertner et al., 2005). That is, for Asian, Black, and Latino Americans, identifying with a common ingroup should predict more positive attitudes toward other racial groups that are included in the common ingroup. And whether the majority group (Whites) is included in the common ingroup or not should not make a difference with regard to attitudes toward other minority groups that are part of both versions of the common ingroup. Furthermore, finding that changes in group identification precede changes in racial attitudes or vice versa in a longitudinal study would challenge the common practice in political psychology of treating identity and/or racial attitudes as exogenous variables (Lee, 2008) or as causally prior to other attitudes of interest (Englehardt, 2020).

My studies provide evidence at the trait level that POC identity is associated with more positive attitudes toward other racial minority groups among Black, Latino, and

Asian Americans, but evidence of effects over time was inconsistent. For Asian Americans (Study 1), POC identification, at both the between- and within-person levels, appears to predict changes in stereotype ratings of other minority groups but not changes in feeling thermometer ratings of those same groups. POC identification also did not consistently predict changes in feeling thermometer ratings of other minority groups among African Americans and Latinos in Study 2. Thus, POC identification is associated with more positive attitudes toward other minority groups, consistent with it being a common ingroup identity, but whether it predicts *improvements* in racial attitudes as predicted by the CIIM might depend on the racial attitude measure in question.

The relationship between American identity and attitudes toward other minority groups was more complicated. American identity was only associated with more positive attitudes toward other racial minority groups at the trait level among Black respondents (Study 2). However, Black and Latino respondents showed some positive cross-lagged effects of American identification on feeling thermometer ratings of other minorities in the CLPM (Study 2), and Latino (Study 2) and Asian (Study 1) respondents showed these effects at the within-person level (in the RI-CLPM). On the other hand, Black respondents showed a marginally significant negative cross-lagged effect at the within-person level (Study 2), in contrast to their positive between-person (trait-level) effects, and Asian respondents showed no significant effects at the between-person level (Study 1), suggesting that individual differences in American identification among Asian Americans might not matter in the trajectories of their attitudes toward other racial minorities.

But American identity was consistently associated with more positive attitudes toward Whites at the trait level and predicted improvements in attitudes toward Whites for all three groups, albeit somewhat inconsistently for Latino respondents. These effects generally did not hold at the within-person level,[1] however, with increases in Asian Americans' American identification actually predicting worsening stereotype ratings. Taken together with the inconsistent results for attitudes toward other minorities, American identity appears to behave like a common ingroup identity that includes Whites for all three racial groups, though this might be primarily at the between-person level, but it is less clear whether American identity includes other minority groups, especially for Latino and Asian Americans.

B. Paradoxical Effects of American Identity

Second, I expected to find support for so-called paradoxical effects of prejudice reduction on minority group members (e.g., Dixon, Durrheim, et al., 2010), but only with a common ingroup identity that includes the majority group (American identity). Thus, I expected Asian, Black, and Latino respondents who identify more strongly as American to express less support for social change that might reduce racial inequality, which I operationalized as support for more liberal immigration policies, criminal justice reform (and relatedly, Black Lives Matter and the George Floyd protests), and affirmative action. This hypothesis follows from social identity theory, which suggests that the same processes of social comparison and social competition underlie prejudice and minority

[1] As discussed in Chapter 4, although Latino respondents in Study 2 showed a significant positive cross-lagged effect between Waves 1 and 2, low statistical power cautions against relying on this result.

group members' motivations to improve their group's status (Tajfel & Turner, 1979), and collective action theory, which proposes relative deprivation as an important pathway connecting group identity and collective action (e.g., van Zomeren et al., 2008). A common ingroup identity that includes the majority group removes the majority group as a relevant comparison group and thus removes a prerequisite for social competition and relative deprivation.

Furthermore, I expected American identity to reduce support for not only policies that benefit one's own racial group but also policies that benefit other minority groups. The paradoxical effects literature has not addressed the effects of common ingroup identity or intergroup contact involving the dominant group on policies that benefit other disadvantaged groups and thus has not made predictions about attitudes toward these policies. But this effect would be consistent with the finding that liking the majority group and perceiving them as fair decreases support for collective action (Saguy et al., 2009): If common ingroup identity leads one to trust the majority group on policies that affect one's own group, that trust can reasonably be expected to extend to policies that affect other minority groups.

My results were consistent with the existence of paradoxical effects primarily at the trait level, and this negative trait-level covariance was consistent among Asian and Latino respondents but not among Black respondents. Additionally, consistent with my expectations, negative trait-level covariances were found for both own-group and other-group policy areas. Cross-lagged effects in the CLPM (which reflect a combination of between- and within-person effects) were found only for Latino and Black respondents and were inconsistent across time lags and (for Black respondents) across items in each policy area, though again, these effects arose for both own-group and other-group policy areas. The only significant within-person effect, however, was a *positive* effect of American identity on Asian Americans' attitudes toward affirmative action, contrary to the negative trait-level covariance and what I expected based on the paradoxical effects literature. Without consistent cross-lagged effects, my studies do not provide strong evidence to support the prediction (based on the paradoxical effects literature) that common ingroup identity predicts *changes* in support for change.

Moreover, the fact that American identity was only inconsistently related to Black respondents' policy attitudes even at the trait level suggests that it might not be merely the common ingroup nature of a national identity like "American" that accounts for paradoxical effects. As with its inconsistent effects on attitudes toward other minority groups, the content of American identity might play a role. For Latino and Asian Americans, "American" might have connotations related to whiteness that are less prevalent among African Americans. And those connotations might lead higher identifiers to 1) exclude other minority groups from or at least perceive them as less prototypical of the common ingroup and 2) align their policy interests more with Whites than with other minorities (i.e., going beyond seeing White authorities as fair or not seeing Whites as a relevant social comparison group). As a result, American identity would 1) not reduce prejudice against other racial minority groups and 2) move policy attitudes in the direction of White Americans' attitudes rather than merely reducing support for policies that benefit minority groups. However, more research is needed to distinguish between paradoxical effects of common ingroup identity and effects of an American identity that connotes whiteness.

C. Disadvantaged Group Identity and Policy Attitudes

Third, group identification is a key predictor of collective action on behalf of the group (e.g., van Zomeren et al., 2008), and both group consciousness and linked fate were developed to help explain the relationship between identity and either group-oriented political behavior (e.g., Miller et al., 1981) or political behavior that is unusually uniform across the group (Dawson, 1994). Consistent with these literatures, I expected to find that racial identification predicts minority group members' support for change in areas that benefit their own racial group: immigration for Asian and Latino respondents and criminal justice reform for Black respondents.

Extending these literatures, I expected a common minority ingroup identity (person of color) to function more like racial identity than American identity in predicting support for change; in other words, POC identity should, if anything, predict increased support for change. This is a proposed boundary condition on the paradoxical effects of prejudice reduction that has not yet been explored in that literature. Nevertheless, it would be consistent with the SIT explanation for why a common ingroup identity that includes the dominant group reduces support for change: Unlike American identity, POC identity does not remove Whites as a relevant comparison group and in fact might make them seem like a more relevant comparison group (cf. Dovidio et al., 2009).

Moreover, I expected POC identity to increase support for change in policy areas that primarily affect other minority groups (criminal justice reform for Asian and Latino respondents, affirmative action for Asian respondents, immigration for Black respondents). These are precisely the policy areas where I did not expect racial identity to increase support for change. This pair of hypotheses follow from the concept of self-relevance appraisals in van Zomeren et al.'s (2012) dual-pathway model of collective action: If a policy affects people of color other than one's racial group, racial identity would not necessarily make the policy self-relevant, but POC identity would. These hypotheses are also consistent with group consciousness models because POC identity should predict linked fate with people of color who are not necessarily part of one's own racial group and make perceived discrimination against other people of color relevant to perceived ingroup interests; as a result, POC identity should predict support for policies that benefit other minority groups experiencing discrimination. Additionally, POC identity predicting support for policies that benefit other minority groups would be consistent with Dixon et al.'s (2015) finding that intergroup contact between disadvantaged groups can increase support for policies that benefit the other disadvantaged group. However, as discussed in Chapter 4 and below, I could not clearly distinguish between the effects of racial and POC identities, because these identities were highly correlated (especially for Black respondents in Study 2), and my panel models examined one identity at a time. Accordingly, more research is needed to fully test the hypothesis that it is specifically POC identity that predicts support for change that primarily benefits other minority groups.

With regard to racial identity, I found positive trait-level associations with own-group policy attitudes among Asian respondents (Study 1) and Black respondents (Study 2) but not among Latino respondents (Study 2). However, I found positive trait-level associations with other-group policy attitudes among all three groups. On own-group issues, only Black respondents showed significant cross-lagged effects of racial identity, but the attitude-identity effect was stronger than the identity-attitude effect (in both the

CLPM and RI-CLPM) for one item, and the positive effect in the CLPM became a negative within-person effect in the RI-CLPM for the other item. Thus, my hypothesis that racial identity would predict increased support for own-group policies was partially supported for African Americans (at least at the between-person level), and the results for Asian Americans are consistent with this hypothesis. However, the results for Latinos are not consistent with this hypothesis. Furthermore, Black and Asian respondents showed at least marginally significant cross-lagged effects of racial identity on at least one other-group policy item— number of immigrants (in the CLPM) for Black respondents and affirmative action (marginally significant in both the CLPM and RI-CLPM) for Asian respondents. The evidence of positive relationships between racial identity and other-group policy attitudes could be an artifact of high correlations between racial and POC identities among Black respondents. But it could also indicate that some of these issues are self-relevant by way of something associated with racial identity, especially for Asian Americans, for whom racial and POC identities were less highly correlated. Again, identity content—in this case, possibly a racial justice activist component, might help explain these unexpected effects.

With regard to POC identity, my results are again mostly consistent with my hypotheses at the trait level (though this is true for only one of the two other-group policy items among Latino respondents). But again, evidence for the directional effects I hypothesized is inconsistent at best. Black respondents showed no significant cross-lagged effects of POC identity on other-group policy attitudes, and Latino respondents showed only inconsistent cross-lagged effects in the CLPM and only on one of the two relevant items. Asian respondents did show significant positive cross-lagged effects of

POC identity in one of the other-group policy areas (affirmative action), in both the CLPM and RI-CLPM, but the only significant cross-lagged effect in the other policy area (criminal justice reform) was a *negative* within-person effect (contrary to both my hypotheses and the positive trait-level covariance). Furthermore, POC identity was positively associated with some own-group policy attitudes. Both Asian and Latino respondents showed positive trait-level correlations between POC identity and immigration attitudes, and this was accompanied by a small cross-lagged effect in the CLPM for Asian respondents and cross-lagged effects in both the CLPM and RI-CLPM on one of the immigration items for Latino respondents. Black respondents also showed a positive association between POC identity and one criminal justice item, though only at the trait level. Again, my results are consistent with my hypotheses at the trait level, but in this case, Study 1 also provides evidence supporting my hypothesis for one respondent group and one policy area—Asian Americans and affirmative action—at both the between- and within-person levels. However, as with racial identity, the own-group versus other group policy area distinction was not supported, especially with regard to Latino and Asian Americans' immigration attitudes, which were more consistently predicted by POC identity than racial identity. That POC identity might influence own-group policy attitudes as well as other-group policy attitudes, though inconsistent with the strongest form of my hypotheses, is not entirely unexpected, considering Pérez's (2021) finding that POC identity predicted *Black*, Latino, and Asian Americans' support for Black Lives Matter. But that POC identity might have a stronger influence than racial identity on Latino and Asian Americans' immigration attitudes is unexpected and raises questions about how these two groups think about immigration.

Finally, the collective action and group consciousness literatures propose mechanisms linking identity to collective action or political attitudes or behavior, though only the collective action literature explicitly calls these mechanisms mediators. I expected to find evidence that these mechanisms overlap, as this would be consistent with the fact that measures of perceived discrimination, perceived group inequality, and assessments of blame have been used to represent both relative deprivation and group consciousness. And I expected the set of mechanisms from both literatures—relative deprivation, perceived discrimination, or system blame; group efficacy; and linked fate—to mediate the relationship between racial identity and support for change. To the extent that POC identity predicts support for change, I also expected these variables to mediate that relationship. And I expected a subset of these variables—namely relative deprivation, perceived discrimination, or system blame—to explain how American identity predicts decreased support for change.

I tested this set of hypotheses primarily in Study 1, which included measures of group-based efficacy, linked fate, perceived discrimination, and relative deprivation. The pilot study and Study 1 indicated that group-based efficacy is distinct from the other collective action and group consciousness variables, at least among Asian Americans. But although the pilot study provided some evidence that the remaining items overlap, Study 1 indicated that linked fate, perceived discrimination, and relative deprivation are empirically distinct. Study 1 did not provide evidence that any of these variables mediate the effects of group identities on Asian Americans' political attitudes. Study 2, which only included measures of linked fate, produced results suggestive of an indirect effect of

African Americans' racial identity on their policy attitudes, but it did not otherwise support my mediation hypotheses.

D. Limitations and Future Research Directions

A major limitation of these studies is the stability of identity importance, racial attitudes, and at least some policy attitudes across the study time frames. Stability was particularly high in Study 1, despite the slightly longer time lags between waves (3-4 weeks versus 1-2 weeks), and the difference was especially noticeable with regard to policy attitudes (and immigration policy attitudes in particular). The higher stability in Study 1 could be a result of aggregation (the number of items aggregated for each variable and the use of factor scores in Study 1) or, in the case of policy attitudes, the relatively high political sophistication of the participant pool from which Study 1 respondents were recruited. Regardless of the source of stability, it might have contributed to the inconsistent cross-lagged effects found in Studies 1 and 2. As Bohrer et al. (2019) note in the context of CLPM, high stability leaves little variance in the variables of interest to be explained by cross-lagged effects. Indeed, the CLPM autoregressive coefficients for identity and racial attitudes in my studies spanned a similar range as those for positive intergroup contact and attitudes toward foreigners in Bohrer et al.'s (2019) study. As a result, it is not surprising that, like Kessler and Mummendey (2002), I found a pattern of trait-level covariances consistent with the relevant theories, but I did not find consistent evidence of a sequential process.

The high stability in my studies could indicate a need for a longitudinal study with a longer time frame (e.g., lags of months or a year rather than a few weeks) or more waves. However, Bohrer et al. (2019) and Sengupta et al. (2020) found similar patterns of stability and lack of change using RI-CLPM with more waves of longer-term longitudinal data—four waves over a year and a half and several waves at one-year intervals, respectively. Their results suggest that a longer time frame and more waves might not solve the stability problem. At the same time, considering that effects of interventions tend to be short-lived, it is unclear how effects that occur over many years in a longitudinal study could inform potential interventions, so a long-term longitudinal study might not be the most fruitful approach to the extent that one is interested in interventions. Furthermore, the high stability, high trait correlations, and lack of within-person effects could indicate that both identity and racial and political attitudes are shaped by a common set of third variables that are not captured by my 2-variable cross-lagged panel models (cf. Kessler & Mummendey, 2002, suggesting that stable individual or situational difference variables outside the model could underlie the high trait covariances among variables related to social identity theory and relative deprivation theory); if so, a longitudinal study over a longer time frame would not address this limitation.

Alternatively, identity and racial attitudes could be more or less crystallized in adults but be more malleable in children, adolescents, and potentially college students, and thus, cross-lagged effects might be more reliably detected in a younger sample. For example, one longitudinal study that found evidence of paradoxical effects of intergroup contact was Tropp et al.'s (2012) study of ethnic minority undergraduates.

Yet another future research direction is to shift to experiments that manipulate some aspect of identity (such as salience) that remains malleable in adults, as much of the early social identity research did, especially if the goal is to develop interventions to increase solidarity between groups. This has not been done with minority group members and common ingroup identity in a way that systematically compares racial, POC, and American identities. Additionally, one could manipulate identity salience and measure a more stable aspect of identity in the same study, as Transue (2007) did with identity importance, to test whether the more stable aspect of identity moderates the effect of identity salience. A study like this involving POC identity would be particularly informative in light of relatively low POC identification among the Asian and Latino respondents in my studies: If making POC identity salient prompts less solidarity among low identifiers, then other intervention strategies might be better suited for these groups.

Another limitation of my studies was the fact that the panel models only examined one identity at a time and thus could not account for cross-identity correlations. When cross-identity correlations are high, as they were particularly for Black respondents' racial and POC identities in Study 2, it is unclear whether cross-lagged effects of either identity in the panel models actually reflect the effects of that identity or if they reflect the effects of the other, correlated identity. Thus, the effects of racial identity on other-group policy attitudes and the effects of POC identity on own-group policy attitudes could mean that the own-group versus other-group distinction is incorrect, but they could also be an artifact of the correlation between racial and POC identification, especially for Black respondents in Study 2. Future research could address this limitation by using models that control for these cross-identity correlations.

As part of a larger study, Study 2 was also limited in the number of items that could be included. Thus, two policy areas—immigration and criminal justice reform—were included instead of three, only linked fate was included out of the potential mediators, and identity was measured by two-item versions of the four-item scale used in Study 1. As a result, I could not examine the relationship between identity and affirmative action attitudes among Black and Latino Americans or test mediation via group efficacy, perceived discrimination, or relative deprivation. Future studies could examine Black and Latino Americans' affirmative action attitudes and/or test different potential mediators of identity-policy attitude effects in these groups

Additionally, the number of Latino respondents in Study 2 was smaller than expected, leading to low statistical power, especially for RI-CLPM. Thus, at least the RI-CLPM results for Latino respondents need to be replicated with a larger sample.

Although I included different measures of identity in Study 1, I only used the identity scales in my panel analyses. That CFA models with the identity scales, ranks, and checklist fit poorly suggests that the rank and checklist items capture something slightly different from the scales. Thus, it is possible that they would show slightly different relationships with racial attitudes and policy attitudes than the identity scales showed. As a follow-up, I could substitute the rank and checklist variables for the identity scale factor scores in the Study 1 analyses. However, these follow-up analyses would involve the same highly stable racial attitude and policy attitude variables, likely leading to similarly unreliable cross-lagged effect estimates.

Finally, my findings with American identity suggest that the content of this identity might be as important or more important than identity strength or centrality in predicting racial minorities' attitudes. Notably, American identity was more consistently associated with attitudes toward Whites than with attitudes toward other minority groups among Asian and Latino respondents, and it was consistently associated with policy attitudes among these two groups but not among Black respondents. Future research could examine associations between American identity and whiteness as an alternative explanation for when it does and does not predict racial and policy attitudes. For example, there is evidence that Asian and White Americans, but not African Americans, implicitly associate the concept of “American” with White faces compared to Black or Asian faces (Devos & Banaji, 2005), and future research could explore whether this association moderates the relationship between Asian Americans’ identification as American and their racial and policy attitudes. Similarly, identity content (e.g., associations with politics or activism) could help explain unexpected effects of racial and POC identity on other-group and own-group policy attitudes, respectively.

E. Conclusions

In summary, across two 3-wave longitudinal studies, I generally found trait-level correlations that were consistent with the literature on common ingroup identity, paradoxical effects, collective action, and group consciousness: Among Asian, Black, and Latino Americans, common ingroup identities (American and POC) were positively associated with attitudes toward other racial groups included in the common ingroup, American identity was generally negatively associated with attitudes toward policies that benefit other minority groups, and disadvantaged group identities (racial and POC) were generally positively associated with attitudes toward policies that benefit minority groups. But with few exceptions (namely, POC identity and Asian Americans’ stereotype ratings of other minority groups and support for affirmative action) my studies offer little support for the directional hypotheses that stem from these theories, i.e., that identity predicts attitude *change*. These findings further highlight the importance of longitudinal studies and especially longitudinal studies that allow for analyses, such as RI-CLPM, that separate between- and within-person cross-lagged effects. My studies join recent longitudinal studies of intergroup contact (Bohrer et al., 2019; Sengupta et al., 2020) that failed to find cross-lagged effects on intergroup attitudes, particularly at the within-person level. The emerging evidence seems to suggest that, to understand how identity and contact come to be related to intergroup attitudes, solidarity, and activism, researchers might be better served by focusing on populations for whom these variables have not stabilized (e.g., college students) or aspects of identity that are malleable enough to be experimentally manipulated.

References

Adorno, T. W., Frenkel-Brunswik, E., Levinson, D. J., & Sanford, R. N. (1950). *The authoritarian personality*. New York, NY: Harper.

Allport, G. W. (1954). *The nature of prejudice*. Menlo Park, CA: Addison-Wesley.

American National Election Studies (2016). Time Series Study. Retrieved from https://electionstudies.org/data-center/

Ansolabehere, S., Rodden, J., & Snyder, J. M. (2008). The strength of issues: Using multiple measures to gauge preference stability, ideological constraint, and issue voting. *American Political Science Review, 102*(2), 215-232. doi:10.1017/S0003055408080210

Bell, M. P., Harrison, D. A., & McLaughlin, M. E. (1997). Asian American attitudes toward affirmative action in employment: Implications for the model minority myth. *The Journal of Applied Behavioral Science*, *33*(3), 356–377. https://doi.org/10.1177/0021886397333006

Bikmen, N. (2011). Asymmetrical effects of contact between minority groups: Asian and Black students in a small college. *Cultural Diversity and Ethnic Minority Psychology*, *17*(2), 186. https://doi.org/10.1037/a0023230

Bohrer, B., Friehs, M.-T., Schmidt, P., & Weick, S. (2019). Contacts between natives and migrants in Germany: Perceptions of the native population since 1980 and an examination of the contact hypotheses. *Social Inclusion*, *7*(4), 320–331. https://doi.org/10.17645/si.v7i4.2429

Bonilla-Silva, E. (2004). From bi-racial to tri-racial: Towards a new system of racial stratification in the USA. *Ethnic and Racial Studies*, *27*(6), 931–950. https://doi.org/10.1080/0141987042000268530

Branscombe, N. R., Schmitt, M. T., & Harvey, R. D. (1999). Perceiving pervasive discrimination among African Americans: Implications for group identification and well-being. *Journal of Personality and Social Psychology*, *77*(1), 135–149. https://doi.org/10.1037/0022-3514.77.1.135

Bullock, J. G., Green, D. P., & Ha, S. E. (2010). Yes, but what's the mechanism? (Don't expect an easy answer). *Journal of Personality and Social Psychology*, *98*(4), 550–558. https://doi.org/10.1037/a0018933

Cakal, H., Hewstone, M., Schwär, G., & Heath, A. (2011). An investigation of the social identity model of collective action and the 'sedative' effect of intergroup contact among Black and White students in South Africa. *British Journal of Social Psychology*, *50*(4), 606–627. https://doi.org/10.1111/j.2044-8309.2011.02075.x

Capers, K. J., & Smith, C. W. (2016). Straddling identities: Identity cross-pressures on Black immigrants' policy preferences. *Politics, Groups, and Identities*, *4*(3), 393–424. https://doi.org/10.1080/21565503.2015.1112823

Carter, E. R., Brady, S. T., Murdock-Perriera, L. A., Gilbertson, M. K., Ablorh, T., & Murphy, M. C. (2019). The racial composition of students' friendship networks predicts perceptions of injustice and involvement in collective action. *Journal of Theoretical Social Psychology*, *3*(1), 49–61. https://doi.org/10.1002/jts5.27

Cho, R. (2020). The effect of minority identity convergence on pan-ethnicity among Asian Americans. *Politics, Groups, and Identities*, *8*(3), 453–470. https://doi.org/10.1080/21565503.2018.1518781

Chong, D., & Rogers, R. (2005). Racial solidarity and political participation. *Political Behavior*, *27*(4), 347–374. https://doi.org/10.1007/s11109-005-5880-5

Cole, D. A., & Maxwell, S. E. (2003). Testing mediational models with longitudinal data: Questions and tips in the use of structural equation modeling. *Journal of Abnormal Psychology*, *112*(4), 558–577. https://doi.org/10.1037/0021-843X.112.4.558

Conover, P. J. (1984). The influence of group identifications on political perception and evaluation. *The Journal of Politics*, *46*(3), 760–785. https://doi.org/10.2307/2130855

Converse, P. E. (1964). The nature of belief systems in mass publics. In D. E. Apter (Ed.), *Ideology and its discontents*. New York: The Free Press of Glencoe

Costin, V., & Vignoles, V. L. (2020). Meaning is about mattering: Evaluating coherence, purpose, and existential mattering as precursors of meaning in life judgments. *Journal of Personality and Social Psychology*, *118*(4), 864–884. https://doi.org/10.1037/pspp0000225

Craig, M. A., DeHart, T., Richeson, J. A., & Fiedorowicz, L. (2012). Do unto others as others have done unto you? Perceiving sexism influences women's evaluations of stigmatized racial groups. *Personality and Social Psychology Bulletin*, *38*(9), 1107–1119. https://doi.org/10.1177/0146167212445210

Craig, M. A., & Richeson, J. A. (2012). Coalition or derogation? How perceived discrimination influences intraminority intergroup relations. *Journal of Personality and Social Psychology, 102*(4), 759-777. https://doi.org/10.1037/a0026481

Craig, M. A., & Richeson, J. A. (2014). More diverse yet less tolerant? How the increasingly diverse racial landscape affects White Americans' racial attitudes. *Personality and Social Psychology Bulletin, 40*(6), 750-761.

Crisp, R. J., Stone, C. H., & Hall, N. R. (2006). Recategorization and subgroup identification: Predicting and preventing threats from common ingroups. *Personality and Social Psychology Bulletin*, *32*(2), 230–243. https://doi.org/10.1177/0146167205280908

Dawson, M. C. (1995). *Behind the mule: Race and class in African-American politics*. Princeton, NJ: Princeton University Press.

Devos, T., & Banaji, M. R. (2005). American = White? *Journal of Personality and Social Psychology*, *88*(3), 447–466. https://doi.org/10.1037/0022-3514.88.3.447

Dixon, J., Durrheim, K., Thomae, M., Tredoux, C., Kerr, P., & Quayle, M. (2015). Divide and rule, unite and resist: Contact, collective action and policy attitudes among historically disadvantaged groups. *Journal of Social Issues*, *71*(3), 576–596. https://doi.org/10.1111/josi.12129

Dixon, J., Durrheim, K., Tredoux, C., Tropp, L., Clack, B., & Eaton, L. (2010). A paradox of integration? Interracial contact, prejudice reduction, and perceptions of racial discrimination. *Journal of Social Issues*, *66*(2), 401–416. https://doi.org/10.1111/j.1540-4560.2010.01652.x

Dixon, J., Levine, M., Reicher, S., & Durrheim, K. (2012). Beyond prejudice: Are negative evaluations the problem and is getting us to like one another more the solution? *Behavioral and Brain Sciences*, *35*(6), 411–425. https://doi.org/10.1017/S0140525X11002214

Dixon, J., Tropp, L. R., Durrheim, K., & Tredoux, C. (2010). "Let them eat harmony": Prejudice-reduction strategies and attitudes of historically disadvantaged groups. *Current Directions in Psychological Science*, *19*(2), 76–80. https://doi.org/10.1177/0963721410363366

Dovidio, J. F., Gaertner, S. L., & Saguy, T. (2009). Commonality and the complexity of "we": Social attitudes and social change. *Personality and Social Psychology Review*, *13*(1), 3–20. https://doi.org/10.1177/1088868308326751

Dovidio, J. F., Gaertner, S. L., Ufkes, E. G., Saguy, T., & Pearson, A. R. (2016). Included but invisible? Subtle bias, common identity, and the darker side of "we." *Social Issues and Policy Review*, *10*(1), 6–46. https://doi.org/10.1111/sipr.12017

Dovidio, J. F., Gaertner, S. L., Validzic, A., Matoka, K., Johnson, B., & Frazier, S. (1997). Extending the benefits of recategorization: Evaluations, self-disclosure, and helping. *Journal of Experimental Social Psychology*, *33*(4), 401–420. https://doi.org/10.1006/jesp.1997.1327

Ellemers, N., Spears, R., & Doosje, B. (1997). Sticking together or falling apart: In-group identification as a psychological determinant of group commitment versus individual mobility. *Journal of Personality and Social Psychology*, *72*(3), 617-626. https://doi.org/10.1037/0022-3514.72.3.617

Ellemers, N., van Knippenberg, A., Vries, N. D., & Wilke, H. (1988). Social identification and permeability of group boundaries. *European Journal of Social Psychology*, *18*(6), 497–513. https://doi.org/10.1002/ejsp.2420180604

Ellemers, N., Wilke, H., & van Knippenberg, A. (1993). Effects of the legitimacy of low group or individual status on individual and collective status-enhancement strategies. *Journal of Personality and Social Psychology*, *64*(5), 766-778.

Engelhardt, A. M. (2020). Racial attitudes through a partisan lens. *British Journal of Political Science*. Advance online publication. https://doi.org/10.1017/S0007123419000437

Foster, M. D., & Matheson, K. (1995). Double relative deprivation: Combining the personal and political. *Personality and Social Psychology Bulletin*, *21*(11), 1167–1177. https://doi.org/10.1177/01461672952111005

Fuller-Rowell, T. E., Ong, A. D., & Phinney, J. S. (2013). National identity and perceived discrimination predict changes in ethnic identity commitment: Evidence from a longitudinal study of Latino college students. *Applied Psychology*, *62*(3), 406–426. https://doi.org/10.1111/j.1464-0597.2012.00486.x

Gaertner, S. L., & Dovidio, J. F. (2005). Categorization, recategorization, and intergroup bias. In J. F. Dovidio, P. Glick, & L. A. Rudman (Eds.), *On the nature of prejudice: Fifty years after Allport* (pp. 71-88). Malden, MA: Blackwell Publishing Ltd.

Gaertner, S. L., Mann, J., Murrell, A., & Dovidio, J. F. (1989). Reducing intergroup bias: The benefits of recategorization. *Journal of Personality and Social Psychology*, *57*(2), 239–249. https://doi.org/10.1037/0022-3514.57.2.239

Gay, C., & Tate, K. (1998). Doubly bound: The impact of gender and race on the politics of Black women. *Political Psychology*, *19*(1), 169–184. https://doi.org/10.1111/0162-895X.00098

Ghandnoosh, N. (2015). *Black lives matter: Eliminating racial inequality in the criminal justice system*. Washington, DC: The Sentencing Project. Retrieved from https://www.sentencingproject.org/publications/black-lives-matter-eliminating-racial-inequity-in-the-criminal-justice-system/

Glasford, D. E., & Calcagno, J. (2012). The conflict of harmony: Intergroup contact, commonality and political solidarity between minority groups. *Journal of Experimental Social Psychology*, *48*(1), 323–328. https://doi.org/10.1016/j.jesp.2011.10.001

Gonzales-Backen, M. A., Meca, A., Lorenzo-Blanco, E. I., Des Rosiers, S. E., Córdova, D., Soto, D. W., … Unger, J. B. (2018). Examining the temporal order of ethnic identity and perceived discrimination among Hispanic immigrant adolescents. *Developmental Psychology*, *54*(5), 929–937. https://doi.org/10.1037/dev0000465

Goodyear-Grant, E., & Tolley, E. (2019). Voting for one's own: Racial group identification and candidate preferences. *Politics, Groups, and Identities*, *7*(1), 131–147. https://doi.org/10.1080/21565503.2017.1338970

Goren, P. & Chapp, C. (2017). Moral power: How public opinion on culture war issues shapes partisan predispositions and religious orientations. *American Political Science Review*, *111*(1), 110-128. doi:10.1017/S0003055416000435

Gordon-Hacker, A., & Gueron-Sela, N. (2020). Maternal use of media to regulate child distress: A double-edged sword? Longitudinal links to toddlers' negative emotionality. *Cyberpsychology, Behavior, and Social Networking*, *23*(6), 400-405. https://doi.org/10.1089/cyber.2019.0487

Górska, P., & Bilewicz, M. (2015). When "a group in itself" becomes "a group for itself": Overcoming inhibitory effects of superordinate categorization on LGBTQ individuals. *Journal of Social Issues*, *71*(3), 554–575. https://doi.org/10.1111/josi.12128

Gurin, P., Miller, A. H., & Gurin, G. (1980). Stratum identification and consciousness. *Social Psychology Quarterly*, *43*(1), 30-47. https://doi.org/10.2307/3033746

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. P. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods*, *20*(1), 102–116. https://doi.org/10.1037/a0038889

Hasan-Aslih, S., Pliskin, R., van Zomeren, M., Halperin, E., & Saguy, T. (2019). A darker side of hope: Harmony-focused hope decreases collective action intentions among the disadvantaged. *Personality and Social Psychology Bulletin*, *45*(2), 209–223. https://doi.org/10.1177/0146167218783190

Haslam, S. A., Oakes, P. J., Reynolds, K. J., & Turner, J. C. (1999). Social identity salience and the emergence of stereotype consensus. *Personality and Social Psychology Bulletin*, *25*(7), 809–818. https://doi.org/10.1177/0146167299025007004

Hogg, M. A., & Turner, J. C. (1987). Intergroup behaviour, self-stereotyping and the salience of social categories. *British Journal of Social Psychology*, *26*(4), 325–340. https://doi.org/10.1111/j.2044-8309.1987.tb00795.x

Hong, Y., & Ratner, K. G. (2020). Minimal but not meaningless: Seemingly arbitrary category labels can imply more than group membership. *Journal of Personality and Social Psychology*. Advance online publication. http://dx.doi.org/10.1037/pspa0000255

Hu, L. & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55.

Huddy, L. (2001). From social to political identity: A critical examination of social identity theory. *Political Psychology*, *22*(1), 127–156. https://doi.org/10.1111/0162-895X.00230

Huddy, L. (2013). From group identity to political cohesion and commitment. In L. Huddy, D. O. Sears, & J. S. Levy (Eds.), *The Oxford Handbook of Political Psychology* (2nd ed.). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199760107.013.0023

Huddy, L., Mason, L., & Aarøe, L. (2015). Expressive partisanship: Campaign involvement, political emotion, and partisan identity. *American Political Science Review*, *109*(1), 1–17. https://doi.org/10.1017/S0003055414000604

Huo, Y. J., Smith, H. J., Tyler, T. R., & Lind, E. A. (1996). Superordinate identification, subgroup identification, and justice concerns: Is separatism the problem; is assimilation the answer? *Psychological Science*, *7*(1), 40–45. https://doi.org/10.1111/j.1467-9280.1996.tb00664.x

Inkelas, K. K. (2003). Caught in the middle: Understanding Asian Pacific American perspectives on affirmative action through Blumer's group position theory.

Journal of College Student Development, *44*(5), 625–643. https://doi.org/10.1353/csd.2003.0053

Jackson, J. W. (1999). How variations in social structure affect different types of intergroup bias and different dimensions of social identity in a multi-intergroup setting. *Group Processes & Intergroup Relations*, *2*(2), 145-173. https://doi.org/10.1177/1368430299022004

Jaśko, K., & Kossowska, M. (2013). The impact of superordinate identification on the justification of intergroup inequalities. *European Journal of Social Psychology*, *43*(4), 255–262. https://doi.org/10.1002/ejsp.1946

Jost, J. T., Becker, J., Osborne, D., & Badaan, V. (2017). Missing in (collective) action: Ideology, system justification, and the motivational antecedents of two types of protest behavior. *Current Directions in Psychological Science*, *26*(2), 99–108. https://doi.org/10.1177/0963721417690633

Jost, J. T., Pelham, B. W., Sheldon, O., & Ni Sullivan, B. (2003). Social inequality and the reduction of ideological dissonance on behalf of the system: Evidence of enhanced system justification among the disadvantaged. *European Journal of Social Psychology*, *33*(1), 13–36. https://doi.org/10.1002/ejsp.127

Jung, C. (2018, November 2). Harvard discrimination trial ends, but lawsuit is far from over. *NPR*. Retrieved from https://www.npr.org

Junn, J., & Masuoka, N. (2008). Identities in context: Politicized racial group consciousness among Asian American and Latino youth. *Applied Developmental Science*, *12*(2), 93–101. https://doi.org/10.1080/10888690801997234

Kadhim, N., Amiot, C. E., & Louis, W. R. (2020). Applying the self-determination theory continuum to unhealthy eating: Consequences on well-being and behavioral frequency. *Journal of Applied Social Psychology*, *50*(7), 381-393.

Kaufmann, K. M. (2003). Cracks in the rainbow: Group commonality as a basis for Latino and African-American political coalitions. *Political Research Quarterly*, *56*(2), 199–210. https://doi.org/10.1177/106591290305600208

Kessler, T., & Mummendey, A. (2002). Sequential or parallel processes? A longitudinal field study concerning determinants of identity-management strategies. *Journal of Personality and Social Psychology*, *82*(1), 75–88. https://doi.org/10.1037/0022-3514.82.1.75

Kim, C. J. (1999). The racial triangulation of Asian Americans. *Politics & Society*, *27*(1), 105–138.

Klandermans, P. G. (2014). Identity politics and politicized identities: Identity processes and the dynamics of protest. *Political Psychology*, *35*(1), 1–22. https://doi.org/10.1111/pops.12167

Koczela, S., & Parr, R. (2017). *Public opinion on criminal justice reform in Massachusetts*. Retrieved from https://massinc.org/wp-content/uploads/2017/06/Public-Opinion-on-Criminal-Justice-Reform-in-Massachusetts.pdf

Kuo, A., Malhotra, N. A., & Mo, C. H. (2014). Why do Asian Americans identify as Democrats? Testing theories of social exclusion and intergroup solidarity. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2423950

Lai, C. K., Marini, M., Lehr, S. A., Cerruti, C., Shin, J.-E. L., Joy-Gaba, J. A., … Nosek, B. A. (2014). Reducing implicit racial preferences: I. A comparative investigation of 17 interventions. *Journal of Experimental Psychology: General*, *143*(4), 1765–1785. https://doi.org/10.1037/a0036260

Leach, C. W., van Zomeren, M., Zebel, S., Vliek, M. L. W., Pennekamp, S. F., Doosje, B., Ouwerkerk, J. W., & Spears, R. (2008). Group-level self-definition and self-investment: A hierarchical (multicomponent) model of in-group identification. *Journal of Personality and Social Psychology*, *95*(1), 144–165. https://doi.org/10.1037/0022-3514.95.1.144

Lee, E. (2015). *The making of Asian America: A history.* New York: Simon & Schuster.

Lee, T. (2008). Race, immigration, and the identity-to-politics link. *Annual Review of Political Science*, *11*(1), 457–478. https://doi.org/10.1146/annurev.polisci.11.051707.122615

Leung, V., & Song, D. (2021). New directions in the study of Asian American politics, Part I: Affirmative action. *PS: Political Science & Politics*, *54*(2), 240–243. https://doi.org/10.1017/S1049096520001985

Levin, S., Sidanius, J., Rabinowitz, J. L., & Federico, C. (1998). Ethnic identity, legitimizing ideologies, and social status: A matter of ideological asymmetry. *Political Psychology*, *19*(2), 373–404. https://doi.org/10.1111/0162-895X.00109

Lien, P. (1994). Ethnicity and political participation: A comparison between Asian and Mexican Americans. *Political Behavior*, *16*(2), 237–264. https://doi.org/10.1007/BF01498879

Lien, P., Conway, M., & Wong, J. (2003). The contours and sources of ethnic identity choices among Asian Americans. *Social Science Quarterly*, *84*(2), 461–481. https://doi.org/10.1111/1540-6237.8402015

Lien, P., Conway, M. M., & Wong, J. (2004). *The politics of Asian Americans: Diversity and community*. Routledge.

Lu, F. (2020). Forging ties: The effect of discrimination on Asian Americans' perceptions of political commonality with Latinos. *Politics, Groups, and Identities*, *8*(3), 595–614. https://doi.org/10.1080/21565503.2018.1528160

Luhtanen, R., & Crocker, J. (2016). A collective self-esteem scale: Self-evaluation of one's social identity: *Personality and Social Psychology Bulletin*, *18*(3), 302-318. https://doi.org/10.1177/0146167292183006

Maertens, R., Roozenbeek, J., Basol, M., & van der Linden, S. (2021). Long-term effectiveness of inoculation against misinformation: Three longitudinal experiments. *Journal of Experimental Psychology: Applied*, *27*(1), 1-16. https://doi.org/10.1037/xap0000315

Maher, P. J., MacCarron, P., & Quayle, M. (2020). Mapping public health responses with attitude networks: The emergence of opinion-based groups in the UK's early COVID-19 response phase. *British Journal of Social Psychology*, *59*(3), 641–652. https://doi.org/10.1111/bjso.12396

Major, B., Gramzow, R. H., McCoy, S. K., Levin, S., Schmader, T., & Sidanius, J. (2002). Perceiving personal discrimination: The role of group status and legitimizing ideology. *Journal of Personality and Social Psychology*, *82*(3), 269-282. https://doi.org/10.1037/0022-3514.82.3.269

Marisol Meraji, S. & Demby, G. (Hosts). (2019, March 20). *Code Switch* [Audio podcast]. NPR. Retrieved from https://www.npr.org/podcasts/510312/codeswitch

Marisol Meraji, S. & Demby, G. (Hosts). (2020, July 29). *Code Switch* [Audio podcast]. NPR. Retrieved from https://www.npr.org/podcasts/510312/codeswitch

Masuoka, N. (2006). Together they become one: Examining the predictors of panethnic group consciousness among Asian Americans and Latinos. *Social Science Quarterly*, *87*(5), 993–1011. https://doi.org/10.1111/j.1540-6237.2006.00412.x

Maxwell, S. E., & Cole, D. A. (2007). Bias in cross-sectional analyses of longitudinal mediation. *Psychological Methods*, *12*(1), 23–44. https://doi.org/10.1037/1082-989X.12.1.23

Maxwell, S. E., Cole, D. A., & Mitchell, M. A. (2011). Bias in cross-sectional analyses of longitudinal mediation: Partial and complete mediation under an autoregressive model. *Multivariate Behavioral Research*, *46*(5), 816–841. https://doi.org/10.1080/00273171.2011.606716

McClain, P. D., Carter, N. M., DeFrancesco Soto, V. M., Lyle, M. L., Grynaviski, J. D., Nunnally, S. C., Scotto, T. J., Kendrick, J. A., Lackey, G. F., & Cotton, K. D. (2006). Racial distancing in a Southern city: Latino immigrants' views of Black Americans. *The Journal of Politics*, *68*(3), 571–584. https://doi.org/10.1111/j.1468-2508.2006.00446.x

Merseth, J. L. (2018). Race-ing solidarity: Asian Americans and support for Black Lives Matter. *Politics, Groups, and Identities*, *6*(3), 337–356. https://doi.org/10.1080/21565503.2018.1494015

Miller, A. H., Gurin, P., Gurin, G., & Malanchuk, O. (1981). Group consciousness and political participation. *American Journal of Political Science*, *25*(3), 494–511. https://doi.org/10.2307/2110816

Mummendey, A., Kessler, T., Klink, A., & Mielke, R. (1999). Strategies to cope with negative social identity: Predictions by social identity theory and relative deprivation theory. *Journal of Personality and Social Psychology*, *76*(2), 229-245. https://doi.org/10.1037/0022-3514.76.2.229

Mummendey, A., Klink, A., Mielke, R., Wenzel, M., & Blanz, M. (1999). Socio-structural characteristics of intergroup relations and identity management strategies: Results from a field study in East Germany. *European Journal of Social Psychology*, *29*(2–3), 259–285. https://doi.org/10.1002/(SICI)1099-0992(199903/05)29:2/3<259::AID-EJSP927>3.0.CO;2-F

Muthén, L. K., & Muthén, B. O. (2002). How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(4), 599–620. https://doi.org/10.1207/S15328007SEM0904_8

Muthén, L. K., & Muthén, B. O. (1998-2019). Mplus User's Guide (8th ed.). Los Angeles, CA: Muthén & Muthén.

Nicholson, H. L., Carter, J. S., & Restar, A. (2020). Strength in numbers: Perceptions of political commonality with African Americans among Asians and Asian Americans in the United States. *Sociology of Race and Ethnicity*, *6*(1), 107–122. https://doi.org/10.1177/2332649218785648

Oakes, P. (2002). Psychological groups and political psychology: A response to Huddy's "Critical examination of social identity theory." *Political Psychology*, *23*(4), 809–824. https://doi.org/10.1111/0162-895X.00308

Orth, U., Clark, D. A., Donnellan, M. B., & Robins, R. W. (2020). Testing prospective effects in longitudinal research: Comparing seven competing cross-lagged models. *Journal of Personality and Social Psychology*, *120*(4), 1013-1034. https://doi.org/10.1037/pspp0000358

Palan, S., & Schitter, C. (2018). Prolific. ac—A subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, *17*, 22-27.

Paluck, E. L., & Green, D. P. (2009). Prejudice reduction: What works? A review and assessment of research and practice. *Annual Review of Psychology*, *60*(1), 339–367. https://doi.org/10.1146/annurev.psych.60.110707.163607

Paluck, E. L., Green, S. A., & Green, D. P. (2019). The contact hypothesis re-evaluated. *Behavioural Public Policy*, *3*(2), 129–158. https://doi.org/10.1017/bpp.2018.25

Pérez, E. (2020, July 2). 'People of color' are protesting. Here's what you need to know about this new identity. *The Washington Post*. https://www.washingtonpost.com/politics/2020/07/02/people-color-are-protesting-heres-what-you-need-know-about-this-new-identity/

Pettigrew, T. F., & Tropp, L. R. (2006). A meta-analytic test of intergroup contact theory. *Journal of Personality and Social Psychology*, *90*(5), 751–783. https://doi.org/10.1037/0022-3514.90.5.751

Phan, N., & Garcia, J. A. (2009). Asian-Pacific-American partisanship: Dynamics of partisan and nonpartisan identities. *Social Science Quarterly, 90*(4), 886–910. https://doi.org/10.1111/j.1540-6237.2009.00668.x

Raiche, G. & Magis, D. (2020). nFactors: Parallel analysis and other non graphical solutions to the Cattell scree test. R package version 2.4.1. https://CRAN.R-project.org/package=nFactors

Ramos, M. R., Cassidy, C., Reicher, S., & Haslam, S. A. (2012). A longitudinal investigation of the rejection–identification hypothesis. *British Journal of Social Psychology*, *51*(4), 642–660. https://doi.org/10.1111/j.2044-8309.2011.02029.x

Reicher, S. (2007). Rethinking the paradigm of prejudice. *South African Journal of Psychology*, *37*(4), 820–834. https://doi.org/10.1177/008124630703700410

Reimer, N. K., Kamble, S. V., Schmid, K., & Hewstone, M. (2020). Intergroup contact fosters more inclusive social identities. *Group Processes & Intergroup Relations*. Advance online publication. https://doi.org/10.1177/1368430220960795

Reimer, N., & Sengupta, N. K. (2020, February 28). Meta-analysis of the “ironic” effects of intergroup contact. In *New developments in intergroup harmony and social change*. Symposium session at the Society for Personality and Social Psychology Convention, New Orleans, LA.

Rodriguez, J., & Gurin, P. (1990). The relationships of intergroup contact to social identity and political consciousness. *Hispanic Journal of Behavioral Sciences*, *12*(3), 235–255. https://doi.org/10.1177/07399863900123001

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1-36. http://www.jstatsoft.org/v48/i02/

Saguy, T., Tausch, N., Dovidio, J. F., & Pratto, F. (2009). The irony of harmony: Intergroup contact can produce false expectations for equality. *Psychological Science*, *20*(1), 114–121. https://doi.org/10.1111/j.1467-9280.2008.02261.x

Samson, F. L. (2015). Asian American attitudes towards a US citizenship path for illegal immigrants: Immigration reform as racialised politics. *Journal of Ethnic and Migration Studies*, *41*(1), 117–137. https://doi.org/10.1080/1369183X.2014.917044

Sanchez, G. R. (2008). Latino group consciousness and perceptions of commonality with African Americans. *Social Science Quarterly*, *89*(2), 428–444. https://doi.org/10.1111/j.1540-6237.2008.00540.x

Sanchez, G. R., & Masuoka, N. (2010). Brown-utility heuristic? The presence and contributing factors of Latino linked fate. *Hispanic Journal of Behavioral Sciences*, *32*(4), 519–531. https://doi.org/10.1177/0739986310383129

Sanchez, G. R., & Vargas, E. D. (2016). Taking a closer look at group identity: The link between theory and measurement of group consciousness and linked fate. *Political Research Quarterly*, *69*(1), 160–174. https://doi.org/10.1177/1065912915624571

Sears, D. O., van Laar, C., Carrillo, M., & Kosterman, R. (1997). Is it really racism?: The origins of White Americans' opposition to race-targeted policies. *The Public Opinion Quarterly*, *61*(1), 16–53.

Sellers, R. M., & Shelton, J. N. (2003). The role of racial identity in perceived racial discrimination. *Journal of Personality and Social Psychology, 84*(5), 1079–1092. https://doi.org/10.1037/0022-3514.84.5.1079

Sengupta, N., Reimer, N. K., Sibley, C. G., & Barlow, F. K. (2020, February 28). Can intergroup contact promote social equality? In *New developments in intergroup harmony and social change*. Symposium session at the Society for Personality and Social Psychology Convention, New Orleans, LA.

Sengupta, N. K., & Sibley, C. G. (2013). Perpetuating one's own disadvantage: Intergroup contact enables the ideological legitimation of inequality. *Personality and Social Psychology Bulletin*, *39*(11), 1391–1403. https://doi.org/10.1177/0146167213497593

Simien, E. M. (2005). Race, gender, and linked fate. *Journal of Black Studies*, *35*(5), 529–550. https://doi.org/10.1177/0021934704265899

Smith, H. J., & Tyler, T. R. (1996). Justice and power: When will justice concerns encourage the advantaged to support policies which redistribute economic resources and the disadvantaged to willingly obey the law? *European Journal of Social Psychology*, *26*(2), 171–200. https://doi.org/10.1002/(SICI)1099-0992(199603)26:2<171::AID-EJSP742>3.0.CO;2-8

Stroebe, K. (2013). Motivated inaction: When collective disadvantage does not induce collective action. *Journal of Applied Social Psychology*, *43*(10), 1997–2006. https://doi.org/10.1111/jasp.12153

Students for Fair Admissions (2018, June 15). Plaintiff's memorandum of reasons in support of its motion for summary judgment. Students for Fair Admissions, Inc. v. President and Fellows of Harvard College, No. 1:14-cv-14176-ADB (D. Mass.).

Tajfel, H., Billig, M. G., Bundy, R. P., & Flament, C. (1971). Social categorization and intergroup behaviour. *European Journal of Social Psychology*, *1*(2), 149–178. https://doi.org/10.1002/ejsp.2420010202

Tajfel, H., & Turner, J. (1979). An integrative theory of intergroup conflict. In W. G. Austin & S. Worchel (Eds.), *The social psychology of intergroup relations* (pp. 33–48). Monterey, CA: Brooks/Cole.

Tausch, N., Becker, J. C., Spears, R., Christ, O., Saab, R., Singh, P., & Siddiqui, R. N. (2011). Explaining radical group behavior: Developing emotion and efficacy routes to normative and nonnormative collective action. *Journal of Personality and Social Psychology*, *101*(1), 129–148. https://doi.org/10.1037/a0022728

Tran, J., & Curtin, N. (2017). Not your model minority: Own-group activism among Asian Americans. *Cultural Diversity and Ethnic Minority Psychology*, *23*(4), 499–507. https://doi.org/10.1037/cdp0000145

Transue, J. E. (2007). Identity salience, identity acceptance, and racial policy attitudes: American national identity as a uniting force. *American Journal of Political Science*, *51*(1), 78–91. https://doi.org/10.1111/j.1540-5907.2007.00238.x

Tropp, L.R., Hawi, D. R., Van Laar, C., & Levin, S. (2012). Cross-ethnic friendships, perceived discrimination, and their effects on ethnic activism over time: A longitudinal investigation of three ethnic minority groups. *British Journal of Social Psychology, 51*, 257-272. https://doi.org/10.1111/j.2044-8309.2011.02050.x

Tropp, L. R., & Pettigrew, T. F. (2005). Relationships between intergroup contact and prejudice among minority and majority status groups. *Psychological Science*, *16*(12), 951–957. https://doi.org/10.1111/j.1467-9280.2005.01643.x

Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory*. Basil Blackwell.

Turner, J. C., Oakes, P. J., Haslam, S. A., & McGarty, C. (1994). Self and collective: Cognition and social context. *Personality and Social Psychology Bulletin*, *20*(5), 454–463. https://doi.org/10.1177/0146167294205002

Turner, J. C., & Reynolds, K. J. (2012). Self-categorization theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of Theories of Social Psychology* (Vol. 2). London: SAGE Publications Ltd.

Ufkes, E. G., Calcagno, J., Glasford, D. E., & Dovidio, J. F. (2016). Understanding how common ingroup identity undermines collective action among disadvantaged-group members. *Journal of Experimental Social Psychology*, *63*(Supplement C), 26–35. https://doi.org/10.1016/j.jesp.2015.11.006

Ufkes, E. G., Dovidio, J. F., & Tel, G. (2015). Identity and collective action among European Kurds. *British Journal of Social Psychology*, *54*(1), 176–186. https://doi.org/10.1111/bjso.12084

University of Minnesota Center for the Study of Political Psychology (2016). Minnesota Presidential Election Panel Study.

van Zomeren, M., Leach, C. W., & Spears, R. (2012). Protesters as “passionate economists”: A dynamic dual pathway model of approach coping with collective disadvantage. *Personality and Social Psychology Review*, *16*(2), 180–199. https://doi.org/10.1177/1088868311430835

van Zomeren, M., Postmes, T., & Spears, R. (2008). Toward an integrative social identity model of collective action: A quantitative research synthesis of three socio-psychological perspectives. *Psychological Bulletin*, *134*(4), 504. https://doi.org/10.1037/0033-2909.134.4.504

Weathers, V. M., & Truxillo, D. M. (2008). Whites' and Asian Americans' perceptions of Asian Americans as targets of affirmative action. *Journal of Applied Social Psychology*, *38*(11), 2737–2758. https://doi.org/10.1111/j.1559-1816.2008.00412.x

Weerd, M. D., & Klandermans, B. (1999). Group identification and political protest: Farmers' protest in the Netherlands. *European Journal of Social Psychology*, *29*(8), 1073–1095. https://doi.org/10.1002/(SICI)1099-0992(199912)29:8<1073::AID-EJSP986>3.0.CO;2-K

White, J. B., Schmitt, M. T., & Langer, E. J. (2006). Horizontal hostility: Multiple minority groups and differentiation from the mainstream. *Group Processes & Intergroup Relations*, *9*(3), 339–358. https://doi.org/10.1177/1368430206064638

Wilkinson, B. C. (2014). Perceptions of commonality and Latino–Black, Latino–White relations in a multiethnic United States. *Political Research Quarterly*, *67*(4), 905–916. https://doi.org/10.1177/1065912914540217

Wright, S. C. (2010). Collective action and social change. In J. F. Dovidio, M. Hewstone, P. Glick, & V. M. Esses (Eds.), *The SAGE Handbook of Prejudice, Stereotyping and Discrimination* (pp. 577-596). London: SAGE Publications Ltd.

Wright, S.C., & Lubensky, M. (2008). The struggle for social equality: Collective action vs. prejudice reduction. In S. Demoulin, J.P. Leyens & J.F. Dovidio (Eds.), *Intergroup misunderstandings: Impact of divergent social realities* (pp. 291–310). New York: Psychology Press.

Wright, S. C., Taylor, D. M., & Moghaddam, F. M. (1990). Responding to membership in a disadvantaged group: From acceptance to collective protest. *Journal of Personality and Social Psychology*, *58*(6), 994–1003. https://doi.org/10.1037/0022-3514.58.6.994

Wu, E. D. (2014). *The color of success: Asian Americans and the origins of the model minority*. Princeton, NJ: Princeton University Press.

Zaller, J. R. (1992). *The nature and origins of mass opinion*. Cambridge: Cambridge University Press.

Zhou, M. (2004). Are Asian Americans becoming “White?” *Contexts*, *3*(1), 29–37. https://doi.org/10.1525/ctx.2004.3.1.29

Zucker, A. N., Weis, A. S., & Richman, L. S. (2019). Grab ‘em by the masculinity: Changes in gendered beliefs and sexism following the 2016 US presidential election. *Politics, Groups, and Identities*, *7*(3), 737-747.

Appendix A: Study Materials

Pilot Study & Study 1 Items

Identity

- Please think about the ways in which you identify yourself, and rank the following identities from the one you identify most strongly with (1) to the one you identify least strongly with (5). (To rank items, drag and drop them into the order you want.)
  - Individual
  - Ethnic group (e.g., Chinese, Vietnamese, or Indian)
  - Asian American
  - Person of color
  - American

- Which of the following identities do you consider important to who you are?
  - Individual
  - Ethnic group
  - Asian American
  - Person of color
  - American

- How important is being Asian American to you?
  - Not important at all
  - Not very important
  - Very important
  - Extremely important
- How well does the term Asian American describe you?
  - Not at all
  - Not very well
  - Very well
  - Extremely well
- When talking about Asian Americans, how often do you use "we" instead of "they"?
  - Never
  - Rarely
  - Some of the time
  - Most of the time
  - All of the time
- To what extent do you think of yourself as being an Asian American?
  - Not at all
  - Very little
  - Somewhat
  - A great deal

- How important is being a person of color to you?
  - Not important at all
  - Not very important
  - Very important
  - Extremely important
- How well does the term person of color describe you?
  - Not at all
  - Not very well
  - Very well
  - Extremely well
- When talking about people of color, how often do you use “we” instead of “they”?
  - Never
  - Rarely
  - Some of the time
  - Most of the time
  - All of the time
- To what extent do you think of yourself as being a person of color?
  - Not at all
  - Very little
  - Somewhat
  - A great deal

- How important is being American to you?
  - Not important at all
  - Not very important
  - Very important
  - Extremely important
- How well does the term American describe you?
  - Not at all
  - Not very well
  - Very well
  - Extremely well
- When talking about Americans, how often do you use “we” instead of “they”?
  - Never
  - Rarely
  - Some of the time
  - Most of the time
  - All of the time
- To what extent do you think of yourself as being an American?
  - Not at all
  - Very little
  - Somewhat
  - A great deal

Feeling Thermometers [Study 1; not included in pilot study]

- We'd like to get your feelings toward some groups in the news these days. We'll give you the name of a group, and we'd I'd like you to rate that group using something we call the feeling thermometer. Ratings between 50 degrees and 100 degrees mean that you feel favorable toward the group. Ratings between 0 degrees and 50 degrees mean that you don't feel favorable toward the group and that you don't care too much for that group. You would rate the group at the 50 degree mark if you don't feel particularly favorable or unfavorable toward the group.

  Please note that you *must move the slider* in order to record a response.
    - Whites
    - Blacks
    - Latinos

Stereotype Items [Study 1 only; not included in pilot study]

- Where would you rate African Americans in general on these scales?
    - Lazy 1 2 3 4 5 6 7 Hardworking
    - Unintelligent 1 2 3 4 5 6 7 Intelligent
- Where would you rate Whites in general on these scales?
    - Lazy 1 2 3 4 5 6 7 Hardworking
    - Unintelligent 1 2 3 4 5 6 7 Intelligent
- Where would you rate Hispanics in general on these scales?
    - Lazy 1 2 3 4 5 6 7 Hardworking
    - Unintelligent 1 2 3 4 5 6 7 Intelligent

Policy Items [All items in Study 1; only immigration & criminal justice items in pilot study]

- Some people say that because of past discrimination, racial minorities should be given preference in hiring and promotion. Others say that such preference is wrong because it gives these groups advantages they haven't earned. What about your opinion -- do you favor or oppose preferential hiring and promotion of minorities?
    - Strongly favor
    - Favor
    - Neither favor nor oppose
    - Oppose
    - Strongly oppose
- To increase the number of black and other underrepresented minority students at their schools, some colleges and universities consider race along with other factors when choosing students. Do you favor or oppose colleges and universities considering race in choosing students?
    - Strongly favor
    - Favor
    - Neither favor nor oppose

  - Oppose
  - Strongly oppose

- Do you think the number of immigrants from foreign countries who are allowed to come to the United States to live should be
  - Increased a lot
  - Increased a little
  - Left the same as it is now
  - Decreased a little
  - Decreased a lot
- Do you think undocumented immigrants in the United States should be allowed to stay or be deported back to their native countries?
  - Strongly favor allowing them to stay
  - Favor allowing them to stay
  - Favor deportation
  - Strongly favor deportation
- Do you favor or oppose detaining undocumented migrants at the border?
  - Strongly favor
  - Favor
  - Neither favor nor oppose
  - Oppose
  - Strongly oppose

- Do you think there are too many people in prison in the United States, not enough people in prison, or is the number of people in prison about right?
  - Too many
  - About the right number
  - Not enough
- There have been some proposals recently to cut the amount of funding police departments receive from state and local governments and using that money to pay for other kinds of first-responder services. Do you favor or oppose cutting the amount of government funding for police departments?
  - Strongly favor
  - Favor
  - Neither favor nor oppose
  - Oppose
  - Strongly oppose
- There have been proposals to eliminate mandatory minimum sentences for certain crimes in order to reduce overly harsh prison sentences. Do you favor or oppose these kinds of proposals?
  - Strongly favor
  - Favor
  - Neither favor nor oppose
  - Oppose
  - Strongly oppose

Potential Mediators

- Do you think what happens generally to other Asians in this country affects what happens in your life?
  - Yes
  - No
- (if Y) Will it affect you a lot, some, or not very much?
  - A lot
  - Some
  - Not very much
- Do you think what happens generally to other people of color in this country affects what happens in your life?
  - Yes
  - No
- (if Y) Will it affect you a lot, some, or not very much?
  - A lot
  - Some
  - Not very much

- Please indicate how much you agree or disagree with the following statements. (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree)
  - Asians are socially and/or economically disadvantaged compared to Whites in the U.S.
  - People of color are socially and/or economically disadvantaged compared to Whites in the U.S.
  - I have less power than Whites do in the U.S.
  - I have fewer opportunities than Whites do in the U.S.
  - America is an open society where individuals of any ethnicity can achieve higher status. [dropped after pilot study]
  - Advancement in American society is possible for individuals of all ethnic groups. [dropped after pilot study]
- How much discrimination or unfair treatment do you think Asians face in the U.S.?
  - None
  - A little
  - Some
  - A lot
- How much discrimination or unfair treatment do you think people of color face in the U.S.?
  - None
  - A little
  - Some
  - A lot

- How much discrimination or unfair treatment do you think you have faced in the U.S. because of your race or ethnicity?
  - None
  - A little
  - Some
  - A lot

- How much do public officials care about what Asian Americans think?
  - Not at all
  - A little
  - A moderate amount
  - A lot
  - A great deal
- How much can Asian Americans affect what the government does?
  - Not at all
  - A little
  - A moderate amount
  - A lot
  - A great deal
- How much do public officials care about what people of color think?
  - Not at all
  - A little
  - A moderate amount
  - A lot
  - A great deal
- How much can people of color affect what the government does?
  - Not at all
  - A little
  - A moderate amount
  - A lot
  - A great deal

- How worried are you about being treated poorly or unfairly because of COVID-19? [not analyzed in Study 1]
  - Not at all worried
  - Somewhat worried
  - Very worried
  - Extremely worried

Demographic/Control Items [pilot study & Study 1 Wave 1]

- What is your self-identified race/ethnicity? (Please check all that apply.)
  - White
  - Hispanic or Latino
  - Black or African American
  - Asian

  - American Indian or Alaska Native
  - Native Hawaiian and other Pacific Islander
  - Other ________
- Which Asian ethnic group(s) do you identify with? (Please check all that apply.)
  - Bangladeshi
  - Cambodian
  - Chinese
  - Filipino
  - Hmong
  - Indian
  - Japanese
  - Korean
  - Laotian
  - Pakistani
  - Vietnamese
  - Bhutanese
  - Burmese
  - Indonesian
  - Malaysian
  - Mongolian
  - Nepali
  - Singaporean
  - Sri Lankan
  - Taiwanese
  - Thai
  - Other Asian
  - None of the above/Not Asian

- Are you currently a U.S. citizen?
  - Yes
  - No

- Were you born in the United States?
  - Yes
  - No
- [if not born in U.S.] What year did you first come to live in the United States? ___

- Are you registered to vote? [dropped after pilot study]
  - Yes
  - No

- Have you voted in a past election in the United States?
  - Yes
  - No
  - Don’t know

- Do you speak a language other than English on a regular basis?
  - I speak another language (not English) primarily.
  - I speak English and another language equally.
  - I speak English primarily but can speak another language.
  - I only speak English.

- What is your gender?
  - Male
  - Female
  - Nonbinary or gender nonconforming
  - Other

- How old are you? ___

- Which of the following is an estimate of your total household income in the past 12 months before taxes?
  - Less than $10,000
  - $10,000 - $14,999
  - $15,000 - $19,999
  - $20,000 - $29,999
  - $30,000 - $39,999
  - $40,000 - $49,999
  - $50,000 - $59,999
  - $60,000 - $69,999
  - $70,000 - $79,999
  - $80,000 - $89,999
  - $90,000 - $99,999
  - $100,000 - $149,999
  - $150,000 - $199,999
  - More than $200,000

- What is the highest level of education you have completed?
  - Less than high school
  - High school diploma or equivalent (GED)
  - Some college
  - 2 year Degree (Associate's)
  - 4 year Degree (Bachelor's)
  - Master's Degree
  - Advanced Degree (PhD, DPHIL, JD, MD, DDS, etc.)

- Below is a seven-point scale on which the political views that people might hold are arranged from extremely liberal to extremely conservative. Where would you place yourself on this scale?
  - Extremely liberal

    - Liberal
    - Slightly liberal
    - Moderate; middle of the road
    - Slightly conservative
    - Conservative
    - Extremely conservative

- Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent, or what?
    - Republican
    - Democrat
    - Independent
    - Other party
- (if Democrat) Would you call yourself a strong Democrat or a not very strong Democrat?
    - Strong Democrat
    - Not very strong Democrat
- (if Republican) Would you call yourself a strong Republican or a not very strong Republican?
    - Strong Republican
    - Not very strong Republican
- (if Independent) Do you think of yourself as closer to the Republican Party or Democratic Party?
    - Democratic
    - Republican
    - Neither

[The political knowledge questions below were dropped after pilot study. Correct answers at the time of the study are in bold.]

- Which party currently has the most members in the U.S. House of Representatives in Washington, D.C.?
    - Republican Party
    - **Democratic Party**
- Would you say that one of the parties is more conservative than the other at the national level?
    - **Republican Party**
    - Democratic Party
    - Neither party is more conservative than the other
- What job or political office is now held by John Roberts?
    - Chair of the Democratic National Committee
    - Senate Majority Leader
    - **Chief Justice of the Supreme Court**
    - Chair of the Republican National Committee
- What job or political office is now held by Mike Pence?
    - House Minority Leader

    - **Vice President of the United States**
    - Secretary of Defense
    - Secretary of State
- How long is the term of office for a U.S. Senator?
    - 2 years
    - 4 years
    - **6 years**
    - 8 years

Study 2 Items

Identity

- How important is being [race (piped from demographics items)] to you?
    - Extremely important
    - Very important
    - Moderately important
    - Slightly important
    - Not at all important
- To what extent do you think of yourself as being [race]?
    - A great deal
    - Quite a bit
    - Somewhat
    - Very little
    - Not at all

- How important is being a person of color to you?
    - Extremely important
    - Very important
    - Moderately important
    - Slightly important
    - Not at all important
- To what extent do you think of yourself as being a person of color?
    - A great deal
    - Quite a bit
    - Somewhat
    - Very little
    - Not at all

- How important is being an American to you?
    - Extremely important
    - Very important
    - Moderately important
    - Slightly important
    - Not at all important
- To what extent do you think of yourself as being an American?

- A great deal
- Quite a bit
- Somewhat
- Very little
- Not at all

[Feeling thermometers were included for Whites, Blacks, Hispanics/Latinos, and Asian-Americans.]

Policy Items

- Do you think the number of immigrants from foreign countries who are allowed to come to the United States to live should be increased, decreased, or kept the same as it is now?
    - Increased a lot
    - Increased a moderate amount
    - Increased a little
    - Kept the same as it is now
    - Decreased a little
    - Decreased a moderate amount
    - Decreased a lot
- Do you support or oppose ending criminal penalties for people crossing the border illegally?
    - Strongly oppose
    - Oppose
    - Somewhat oppose
    - Neither support nor oppose
    - Somewhat support
    - Support
    - Strongly support

- In general do you support or oppose the protests that have occurred in recent months in response to the death of George Floyd and others in the African American community?
    - Strongly support
    - Support
    - Somewhat support
    - Neither support nor oppose
    - Somewhat oppose
    - Oppose
    - Strongly oppose
- How do you feel about Black Lives Matter?
    - Very positive
    - Positive
    - Neutral
    - Negative

    - Very negative
- If a criminal offense, even a drug offense, carries a "mandatory minimum" sentence, a judge must give the defendant at least the mandatory minimum sentence, even if the judge believes that the sentence is too long. Some people think that mandatory minimum sentences should be given in all cases where they apply, with no exceptions. Others say that a judge should be able to make an exception and give a shorter sentence (i.e., one below the mandatory minimum sentence) if the judge finds compelling circumstances. What do you think?
    - Mandatory minimum sentences should be given in all cases where they apply, with no exceptions.
    - Even where a mandatory minimum sentence applies, a judge should have the freedom to give a shorter sentence if the judge finds compelling circumstances.

[Linked fate items were included for race (piped from demographics questions) and POC, as in Study 1.]

Demographic/Control Items (Wave 1 only except partisan identity measure W1 & W3)

- Which racial or ethnic group best describes you? Please select all that apply.
    - Asian
    - Black
    - Hispanic/Latino
    - White
    - Native American
    - Middle Eastern
    - Other

- What is your gender?
    - Man
    - Woman
    - Other
    - Prefer not to say

- We hear a lot of talk these days about liberals and conservatives. Here is a seven-point scale on which the political views that people might hold are arranged from extremely liberal to extremely conservative. Where would you place yourself on this scale?
    - Extremely liberal
    - Liberal
    - Slightly liberal
    - Moderate; middle of the road
    - Slightly conservative
    - Conservative
    - Extremely conservative
- [Partisan identity was measured as in Study 1.]

- Additional demographic information provided by YouGov
  - In what year were you born?
  - What is the highest level of education you have completed?
    - No HS
    - High school graduate
    - Some college
    - 2-year
    - 4-year
    - Post-grad
  - Which of these statements best describes you?
    - I am an immigrant to the USA and a naturalized citizen
    - I am an immigrant to the USA but not a citizen
    - I was born in the USA but at least one of my parents is an immigrant
    - My parents and I were born in the USA but at least one of my grandparents was an immigrant
    - My parents, grandparents and I were all born in the USA
  - Thinking back over the last year, what was your family's annual income?
    - Less than $10,000
    - $10,000 - $19,999
    - $20,000 - $29,999
    - $30,000 - $39,999
    - $40,000 - $49,999
    - $50,000 - $59,999
    - $60,000 - $69,999
    - $70,000 - $79,999
    - $80,000 - $99,999
    - $100,000 - $119,999
    - $120,000 - $149,999
    - $150,000 - $199,999
    - $200,000 - $249,999
    - $250,000 - $349,999
    - $350,000 - $499,999
    - $500,000 or more
    - Prefer not to say

Appendix B: Panel Model Power Analyses

To determine target sample sizes before beginning participant recruitment for Study 1, I did power analyses using Monte Carlo simulation in Mplus, following Muthén and Muthén's (2002) guidelines and adapting code from Chapter 12 of the Mplus User's Guide (Muthén and Muthén, 1998-2017). Because the CLPM is nested under the RI-CLPM and has fewer parameters to estimate (Hamaker et al., 2015), it should not require as large of a sample as the RI-CLPM. Therefore, I did power analyses only for the RI-CLPM and the longitudinal mediation model.

For the RI-CLPM, I examined power to detect a cross-lagged effect of identity on attitudes of $\beta = 0.2$ when there is also a cross-lagged reverse effect of attitude on identity of $\beta = 0.1$. Across simulations, I assumed an intraclass correlation coefficient (ICC) of 0.6 for group identification, based on Kessler and Mummendey's (2002) finding that trait variance accounted for 58% of the variance in East Germans' group identification over a year. (I used this number because it was the only available estimate of trait versus state variance in identification.) I varied the ICC for attitudes, which I expected to be lower for policy attitudes than for racial attitudes; the autoregression coefficients; and the between- and within-person identity-attitude covariances.

For the longitudinal mediation model, I examined power to detect the identity-to-mediator cross-lagged effects (*a*), the mediator-to-attitude cross-lagged effects (*b*), and the indirect effect of identity on attitudes (*ab*), adapting code from Muthén and Schultzberg (2017) and the chapter 12 examples from the Mplus User's Guide to run the simulations. Across simulations, I set the variances of all observed variables to 1, the covariances among the variables in Wave 1 and the error covariances among the variables in Waves 2 and 3 to 0.25, and the autoregression coefficients for identity and attitudes to 0.6 and 0.3, respectively. I also set the cross-lagged coefficients of identity on the mediator to $a = 0.2$ and the cross-lagged coefficients of identity on attitudes (the direct effect) to $c = 0.1$ across simulations. I varied the cross-lagged coefficient of the mediator on attitudes ($b = 0.2$ vs. $b = 0.1$), the existence of reverse paths (all set to $b = 0.1$), the autoregression coefficient for the mediator (set at either 0.5 or 0.3), and whether the model assumed stationarity.

All simulations for both models were run with 10,000 replications and sample sizes from 400 up to 600 or a sample size that gave approximately .80 power for the effect(s) of interest (i.e., the cross-lagged identity-to-attitude coefficients in the RI-CLPM and the *a*, *b*, and *ab* effects in the mediation model). For each type of model, I used two seeds across parameter and sample size combinations, and I set the seeds by rolling dice: a d6 for the number of digits (1-6) and then a d10 for the value of each digit (0-9). Details of the input and results are included in Tables SM1 (RI-CLPM) and SM2 (mediation model).

Based on the RI-CLPM simulations, between 500 and 600 participants are needed to detect a cross-lagged effect of $\beta = 0.2$ with approximately power = .80. Further support for this sample size range comes from the fact that it is more than twice the sample size that Hamaker et al. (2015) used for simulations (N = 200, "which seems to be an acceptable sample size for a two-wave CLPM", p. 109) and thus should be reasonable for my CLPM models. A sample size between 400 and 500 appears to be sufficient to detect *a*, *b*, and *ab* effects in the mediation model. As Cole and Maxwell (2003) note, however, there has not been much work on sample sizes and power for longitudinal mediation analysis. But Wang & Xue's (2016) simulations seem to suggest that N = 500 is reasonable for detecting mediation effects for 2- and 5-wave longitudinal studies that are more complex than my models, if the effects of X on M and M on Y are sufficiently large. Based on my analyses and the existing literature, I decided on a target sample size of 500-600 participants who complete all three waves of the study.

Table A1

RI-CLPM Power Analysis Details (Cross-lagged identity-to-attitude effect = 0.2; Cross-lagged attitude-to-identity effect = 0.1)

ICC: att	ID-ID	att-att	trait corr	state corr	N	seed	RMSEA (sd)	SRMR (sd)	param bias ok[a]	SE bias ok[b]	power: att1-ID2	power: att2-ID3	power: ID1-att2	power: ID2-att3
0.6	0.3	0.4	0.25	0.25	400	6676	.012 (.016)	.038 (.011)	y	n	.203	.23	.663	.739
						8697	.012 (.016)	.038 (.011)	y	n	.205	.243	.673	.732
					500	6676	.011 (.014)	.034 (.010)	y	y	.244	.273	.757	.829
						8697	.011 (.014)	.034 (.010)	y	n	.238	.276	.763	.821
					550	6676	.011 (.014)	.032 (.009)	y	y	.26	.297	.793	.86
						8697	.010 (.014)	.032 (.009)	y	n	.254	.301	.805	.854
0.5	0.3	0.4	0.4	0.25	400	6676	.012 (.016)	.037 (.011)	y	n	.292	.3	.59	.702
						8697	.012 (.016)	.037 (.010)	y	n	.294	.314	.604	.694
					500	6676	.011 (.014)	.033 (.009)	y	n	.349	.352	.682	.798
						8697	.011 (.014)	.033 (.009)	y	n	.339	.358	.693	.787
			0.25	0.4	400	6676	.012 (.016)	.037 (.011)	y	n	.279	.282	.588	.686

						8697	.012	.037	y	n	.282	.295	.602	.677
							(.016)	(.010)						
					500	6676	.011	.033	y	n	.335	.337	.683	.786
							(.014)	(.009)						
0.5	0.3	0.4	0.25	0.4	500	8697	.011	.033	y	n	.327	.34	.697	.772
							(.014)	(.009)						
			0.25	0.25	400	6676	.012	.037	y	n	.285	.29	.593	.695
							(.016)	(.011)						
						8697	.012	.037	y	n	.288	.305	.605	.687
							(.016)	(.010)						
					500	6676	.011	.033	y	n	.343	.343	.684	.792
							(.014)	(.009)						
						8697	.011	.033	y	n	.334	.349	.698	.779
							(.014)	(.009)						
					600	6676	.010	.030	y	n	.4	.39	.761	.859
							(.013)	(.008)						
						8697	.010	.030	y	n	.391	.402	.773	.852
							(.013)	(.008)						
			0.25	0.1	400	6676	.012	.037	y	n	.289	.297	.589	.701
							(.016)	(.010)						
						8697	.012	.037	y	n	.29	.312	.601	.693
							(.016)	(.010)						
					500	6676	.011	.033	y	n	.346	.35	.68	.794
							(.014)	(.009)						
						8697	.011	.033	y	n	.335	.355	.692	.786
							(.014)	(.009)						
			0.1	0.25	400	6676	.012	.037	y	n	.282	.28	.595	.692
							(.016)	(.010)						
						8697	.012	.037	y	n	.282	.296	.608	.683
							(.016)	(.010)						

					500	6676	.011 (.014)	.033 (.009)	y	n	.34	.339	.689	.789
						8697	.011 (.014)	.033 (.009)	y	n	.332	.344	.702	.777
0.5	0.3	0.3	0.25	0.25	400	6676	.012 (.016)	.037 (.010)	y	n	.291	.289	.547	.634
		0.3	0.25	0.25	400	8697	.012 (.016)	.037 (.010)	y	n	.293	.304	.562	.624
					500	6676	.011 (.014)	.033 (.009)	y	y	.349	.345	.638	.732
					500	8697	.011 (.014)	.033 (.009)	y	n	.339	.349	.654	.723
					600	6676	.010 (.013)	.030 (.008)	y	y	.406	.392	.717	.803
					600	8697	.010 (.013)	.030 (.008)	y	y	.394	.404	.728	.801
	0.1	0.3	0.25	0.25	400	6676	.012 (.016)	.038 (.010)	n	n	.256	.245	.557	.675
						8697	.012 (.016)	.038 (.010)	n	n	.259	.258	.574	.668
					500	6676	.011 (.014)	.034 (.009)	y	y	.308	.291	.647	.768
						8697	.011 (.014)	.034 (.009)	y	y	.303	.296	.662	.762
					600	6676	.010 (.013)	.031 (.008)	y	y	.362	.324	.724	.838
						8697	.010 (.013)	.031 (.008)	y	y	.35	.335	.734	.829
0.4	0.3	0.4	0.25	0.25	400	6676	.012 (.016)	.037 (.010)	y	n	.38	.359	.541	.654

						8697	.012	.037	y	n	.384	.375	.556	.646
							(.016)	(.010)						
					500	6676	.011	.033	y	n	.461	.424	.629	.751
							(.014)	(.009)						
0.4	0.3	0.4	0.25	0.25	500	8697	.011	.033	y	n	.447	.433	.643	.744
							(.014)	(.009)						
					600	6676	.010	.030	y	n	.533	.485	.706	.822
							(.013)	(.008)						
						8697	.010	.030	y	n	.512	.495	.719	.82
							(.013)	(.008)						

Note: All simulations used ID-attitude cross-lagged coefficient = 0.2 (the parameter of interest), attitude-ID cross-lagged coefficient = 0.1, identity ICC = .6.

[a] Following Muthén and Muthén's (2002) guidelines, the average estimate for each parameter should not differ from the actual parameter value by more than 10% of the actual parameter value.
[b] Following Muthén and Muthén's (2002) guidelines, the average standard error for each parameter estimate should not differ from the standard deviation of the estimates of that parameter over the set of replications by more than 10% of the standard deviation. For the parameters of interest (the cross-lagged coefficients from state identity to state attitude and vice versa), the standard error bias should not exceed 5% of the standard deviation. Note that most of these simulations do not meet the standard error bias criterion, and therefore, these power estimates might be less accurate than is ideal.

Table A2

Mediation Model Power Analysis Details

b	***m***	**reverse paths**	**statio narity**	**N**	**seed**	**RMSEA (sd)**	**SRMR (sd)**	**param bias ok**[a]	**SE bias ok**[b]	**power *a* avg**[c]	**power *b* avg**	**power *c* avg**	**power *ab***[d]
0.2	0.5	0	y	400	1858	.010 (.012)	.042 (.007)	y	y	1	1	.83	1
		0.1	y	400	1858	.010 (.012)	.039 (.007)	y	y	1	1	.823	1
					537	.011 (.013)	.039 (.007)	y	y	1	1	.823	.999
			n	400	1858	.011 (.013)	.035 (.007)	y	y	.978	.974	.528	.894
					537	.011 (.013)	.035 (.007)	y	y	.978	.973	.542	.899
	0.3	0.1	y	400	1858	.010 (.012)	.040 (.006)	y	y	1	1	.826	1
					537	.011 (.013)	.040 (.007)	y	y	1	.999	.825	.999
0.1	0.5	0	y	400	1858	.010 (.012)	.042 (.007)	y	y	1	.832	.825	.809
					537	.010 (.012)	.042 (.007)	y	y	1	.839	.825	.815
		0.1	y	400	1858	.010 (.012)	.040 (.007)	y	y	1	.806	.822	.783
					537	.011 (.013)	.040 (.007)	y	y	1	.812	.825	.784

				500	1858	.009	.035	y	y	1	.884	.897	.873
						(.011)	(.006)						
					537	.009	.035	y	y	1	.886	.896	.873
						(.011)	(.006)						
0.1	0.5	0.1	n	400	1858	.011	.035	y	y	.978	.52	.53	.379
						(.013)	(.007)						
					537	.011	.035	y	y	.978	.518	.534	.387
						(.013)	(.007)						
				500	1858	.010	.032	y	y	.993	.614	.622	.521
						(.012)	(.006)						
					537	.010	.031	y	y	.992	.613	.624	.529
						(.012)	(.006)						
				600	1858	.009	.029	y	y	.998	.69	.704	.64
						(.011)	(.005)						
					537	.009	.029	y	y	.998	.688	.698	.643
						(.011)	(.005)						
	0.3	0.1	y	400	1858	.010	.041	y	y	1	.78	.826	.751
						(.012)	(.006)						
					537	.011	.041	y	y	1	.779	.826	.752
						(.013)	(.006)						
				500	1858	.009	.036	y	y	1	.863	.897	.849
						(.011)	(.006)						
					537	.009	.036	y	y	1	.862	.897	.85
						(.011)	(.006)						
0.05	0.5	0	y	400	1858	.010	.043	y	y	1	.321	.824	.292
						(.012)	(.007)						

[a] Following Muthén and Muthén's (2002) guidelines, the average estimate for each parameter should not differ from the actual parameter value by more than 10% of the actual parameter value.

[b] Following Muthén and Muthén's (2002) guidelines, the average standard error for each parameter estimate should not differ from the standard deviation of the estimates of that parameter over the set of replications by more than 10% of the standard deviation. For the parameters of interest (the cross-lagged coefficients from state identity to state attitude and vice versa), the standard error bias should not exceed 5% of the standard deviation.

[c] When stationarity is assumed, average power is equal to power to detect the relevant effect from Wave 1 to Wave 2 and from Wave 2 to Wave 3. When stationarity is not assumed, power to detect the effect from Wave 1 to Wave 2 and power to detect the effect from Wave 2 to Wave 3 were averaged.

[d] When stationarity is assumed, *ab* is the product of *a* and *b*. When stationarity is not assumed, *ab* is the product of *a* from Wave 1 to Wave 2 and *b* from Wave 2 to Wave 3.

Appendix C: Additional Panel Model Results

Table A3

Study 1 Asian American Identity & Nonwhite FT Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.821 (.023)***/ *.818*	.860 (.015)***/ *.831*	.798 (.024)***/ *.792*	.780 (.054)***/ *.784*	.842 (.015)***/ *.809*	.830 (.034)***/ *.807*	-.058 (.188)/- *.056*	-.035 (.089)/-*.049*
	W1 FTs	.026 (.022)/*.027*	.006 (.014)/*.006*	.026 (.024)/*.027*	.030 (.057)/*.031*	.016 (.015)/*.016*	.002 (.036)/*.002*	.097 (.106)/*.129*	.059 (.066)/*.098*
W2 FTs	W1 ID	.020 (.026)/*.019*	.007 (.017)/*.006*	.027 (.027)/*.025*	.016 (.058)/*.015*	.006 (.018)/*.006*	-.059 (.036)/-*.055*	.072 (.184)/*.047*	.009 (.095)/*.006*
	W1 FTs	.838 (.025)***/ *.804*	.828 (.017)***/ *.802*	.798 (.026)***/ *.767*	.746 (.062)***/ *.732*	.805 (.018)***/ *.771*	.773 (.038)***/ *.751*	.436 (.129)**/ *.383*	.469 (.069)***/ *.412*
W3 ID	W2 ID	.889 (.020)***/ *.877*	.860 (.015)***/ *.875*	.876 (.021)***/ *.866*	.862 (.047)***/ *.839*	.842 (.015)***/ *.861*	.830 (.034)*** /*.832*	.352 (.095)***/ *.329*	-.035 (.089)/-*.031*
	W2 FTs	-.008 (.018)/-*.009*	.006 (.014)/*.006*	.008 (.020)/*.009*	-.015 (.048)/-*.016*	.016 (.015)/*.017*	.002 (.036)/*.002*	.010 (.065)/*.013*	.059 (.066)/*.100*
W3 FTs	W2 ID	-.008 (.024)/-*.007*	.007 (.017)/*.006*	-.016 (.026)/-*.015*	-.106 (.048)*/- *.101*	.006 (.018)/*.006*	-.059 (.036)/-*.058*	-.066 (.091)/- *.046*	.009 (.095)/*.005*
	W2 FTs	.821 (.022)***/ *.831*	.828 (.017)***/ *.830*	.810 (.025)***/ *.820*	.787 (.050)***/ *.803*	.804 (.018)***/ *.815*	.773 (.038)***/ *.793*	.481 (.071)***/ *.500*	.469 (.069)***/ *.496*

trait cov							.004 (.001)**/ *.151*	.004 (.001)**/ *.150*
W1 ID-FT cov	.005 (.001)***/ *.143*	.005 (.001)***/ *.143*	.005 (.001)***/ *.147*	.006 (.003)$^{+}$/*.175*	.005 (.001)*** /*.143*	.006 (.003)$^{+}$/*.175*	.001 (.001)/*.121*	.000 (.001)/*.039*
W2 ID-FT cov	.001 (.000)*/*.080*	.001 (.000)*/*.079*	.001 (.000)*/*.080*	.001 (.001)/*.070*	.001 (.000)$^{+}$/*.078*	.001 (.001)/*.059*	.001 (.001)/*.159*	.001 (.001)/*.183*
W3 ID-FT cov	.000 (.000)/*.025*	.000 (.000)/*.024*	.000 (.000)/*.029*	.001 (.001)$^{+}$/*.159*	.000 (.000)/*.027*	.001 (.001)$^{+}$/*.152*	-.000 (.000)/-*.042*	-.000 (.000)/-*.013*
params	17	17	149	149	149	149	20	20
N	631	631	613	126	613	126	631	631
CFI	.962	.961	.973	.979	.972	.978	1.000	.998
RMSEA	.218	.156	.218	.204	.156	.146	.000	.046
SRMR	.028	.033	.010	.010	.012	.014	.000	.026
Chisq (df)	123.907 (4)***	130.726 (8)***	120.394 (4)***	24.928 (4)***	127.989 (8)***	29.519 (8)***	0.001 (1)	11.546 (5)*
Chisq test		6.819 (4)			7.595 (4)	4.591 (4)		11.545 (4)*

Note: In Study 1 tables, CLPM Model 1 = model without covariates; CLPM Model 2 = model with covariates, including foreign-born variable; CLPM Model 3 = model with covariates, including age of arrival in U.S.

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A4

Study 1 POC Identity & Nonwhite FT Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.889 (.019)***/ *.889*	.900 (.013)***/ *.890*	.877 (.020)***/ *.874*	.874 (.049)***/ *.852*	.888 (.015)***/ *.877*	.851 (.033)***/ *.849*	.099 (.213)/ *.099*	.251 (.134)+/*.252*
	W1 FTs	.024 (.023)/*.019*	.031 (.017)+/*.024*	.012 (.025)/*.010*	.121 (.059)*/*.104*	.020 (.018)/ *.016*	.031 (.040)/ *.027*	.067 (.106)/ *.083*	.058 (.063)/ *.068*
W2 FTs	W1 ID	.057 (.020)**/ *.069*	.031 (.014)*/*.038*	.033 (.021)/*.040*	.118 (.050)*/*.132*	.016 (.015)/ *.019*	.045 (.032)/ *.050*	.283 (.190)/ *.201*	.006 (.082)/ *.005*
	W1 FTs	.820 (.025)***/ *.787*	.818 (.017)***/ *.793*	.796 (.026)***/ *.764*	.731 (.060)***/ *.717*	.802 (.018)***/ *.769*	.751 (.039)***/ *.736*	.408 (.124)**/ *.358*	.463 (.070)***/ *.409*
W3 ID	W2 ID	.914 (.019)***/ *.884*	.900 (.013)***/ *.885*	.901 (.021)***/ *.870*	.840 (.024)***/ *.861*	.888 (.015)***/ *.868*	.851 (.033)***/ *.840*	.272 (.136)*/*.217*	.251 (.134)+/*.234*
	W2 FTs	.037 (.023)/*.030*	.031 (.017)+/*.024*	.027 (.025)/*.022*	-.012 (.030)/-*.010*	.020 (.018)/ *.016*	.031 (.040)/ *.027*	.174 (.094)+/*.196*	.058 (.063)/ *.071*
W3 FTs	W2 ID	.008 (.019)/*.009*	.031 (.014)*/*.039*	-.000 (.021)/- *.000*	-.003 (.021)/-*.003*	.016 (.015)/ *.020*	.045 (.032)/ *.051*	-.070 (.094)/-*.052*	.006 (.082)/ *.005*
	W2 FTs	.817 (.023)***/ *.827*	.818 (.017)***/ *.819*	.807 (.025)***/ *.817*	.796 (.026)***/ *.787*	.802 (.018)***/ *.813*	.751 (.039)***/ *.769*	.495 (.074)***/ *.513*	.463 (.070)***/ *.488*

trait cov							.012 (.002)***/ *.321*	.013 (.002)***/ *.344*
W1 ID-FT cov	.013 (.002)***/ *.290*	.013 (.002)***/ *.290*	.013 (.002)***/ *.283*	.012 (.004)**/ *.276*	.013 (.002)***/ *.283*	.012 (.004)***/ *.276*	.002 (.001)/ *.176*	.001 (.001)/ *.099*
W2 ID-FT cov	.001 (.001)**/ *.114*	.001 (.001)**/ *.112*	.001 (.000)**/ *.104*	.001 (.001)/ *.062*	.001 (.000)*/*.104*	.001 (.001)/ *.064*	.003 (.001)*/*.294*	.001 (.001)/ *.138*
W3 ID-FT cov	.001 (.000)/*.049*	.001 (.000)/ *.047*	.001 (.000)/*.045*	.000 (.001)/ *.133*	.001 (.000)/ *.044*	.001 (.001)/ *.133*	.000 (.001)/ *.029*	.000 (.001)/ *.026*
params	17	17	149	149	149	149	20	20
N	631	631	613	126	613	126	631	631
CFI	.971	.971	.978	.986	.978	.982	1.000	1.000
RMSEA	.203	.145	.206	.168	.145	.137	.000	.017
SRMR	.023	.027	.008	.007	.009	.014	.002	.014
Chisq (df)	108.279 (4)***	113.591 (8)***	108.152 (4)***	18.200 (4)**	110.501 (8)***	26.942 (8)**	0.144 (1)	5.951 (5)
Chisq test		5.312 (4)			2.349 (4)	8.742 (4)$^{+}$		5.807 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A5

Study 1 American Identity & Nonwhite FT Panel Model Results

		CLPM Model 1	CLPM Model 1, stationarity	CLPM Model 2	CLPM Model 3	CLPM Model 2, stationarity	CLPM Model 3, stationarity	RI-CLPM	RI-CLPM, stationarity
W2 ID	W1 ID	.904 (.016)***/ *.916*	.926 (.011)***/ *.921*	.902 (.017)***/ *.912*	.899 (.033)***/ *.915*	.913 (.012)***/ *.918*	.922 (.023)***/ *.923*	-.194 (.216)/-*.225*	-.200 (.127)/-*.285*
	W1 FTs	.034 (.016)*/*.034*	.003 (.011)/ *.003*	.040 (.017)*/*.040*	.040 (.041)/ *.037*	.011 (.012)/ *.011*	-.018 (.027)/-*.016*	.211 (.087)*/*.461*	.149 (.050)**/ *.388*
W2 FTs	W1 ID	.010 (.024)/ *.009*	-.001 (.017)/-*.001*	.040 (.026)/ *.039*	.020 (.050)/ *.022*	.015 (.018)/ *.014*	-.038 (.032)/-*.041*	.221 (.361)/ *.103*	.273 (.137)*/*.135*
	W1 FTs	.840 (.025)***/ *.806*	.828 (.016)***/ *.803*	.798 (.026)***/ *.767*	.748 (.061)***/ *.733*	.803 (.018)***/ *.770*	.765 (.038)***/ *.744*	.441 (.134)**/ *.389*	.427 (.076)***/ *.387*
W3 ID	W2 ID	.946 (.015)***/ *.930*	.926 (.011)***/ *.927*	.925 (.016)***/ *.911*	.949 (.032)***/ *.921*	.913 (.012)***/ *.906*	.922 (.023)***/ *.911*	.044 (.220)/ *.035*	-.200 (.127)/-*.131*
	W2 FTs	-.024 (.015)$^{+}$/- *.025*	.003 (.011)/ *.003*	-.015 (.016)/-*.016*	-.071 (.038)$^{+}$/- *.064*	.011 (.012)/ *.011*	-.018 (.027)/-*.016*	.052 (.091)/ *.104*	.149 (.050)**/ *.280*
W3 FTs	W2 ID	-.011 (.023)/-*.010*	-.001 (.017)/-*.001*	-.010 (.025)/-*.010*	-.080 (.042)$^{+}$/- *.088*	.015 (.018)/ *.014*	-.038 (.032)/-*.042*	.111 (.153)/ *.046*	.273 (.137)*/*.098*
	W2 FTs	.821 (.022)***/ *.831*	.828 (.016)***/ *.830*	.809 (.025)***/ *.818*	.781 (.049)***/ *.797*	.803 (.018)***/ *.814*	.765 (.038)***/ *.787*	.473 (.070)***/ *.491*	.427 (.076)***/ *.441*

trait cov							.002 (.002)/ *.073*	.002 (.001)/ *.073*
W1 ID-FT cov	.004 (.001)*/*.095*	.004 (.001)*/*.095*	.004 (.002)*/*.101*	.003 (.004)/ *.060*	.004 (.002)*/*.101*	.003 (.004)/ *.060*	.001 (.001)/ *.204*	.001 (.000)/ *.083*
W2 ID-FT cov	.000 (.000)/ *.017*	.000 (.000)/ *.018*	.000 (.000)/ *.026*	.002 (.001)*/*.178*	.000 (.000)/ *.025*	.001 (.001)$^{+}$/*.167*	.001 (.001)/ *.270*	.002 (.001)*/*.457*
W3 ID-FT cov	-.000 (.000)/-*.015*	-.000 (.000)/-*.015*	-.000 (.000)/-*.007*	.001 (.001)/ *.146*	-.000 (.000)/-*.009*	.001 (.001)/ *.135*	-.000 (.000)/-*.052*	.000 (.000)/ *.005*
params	17	17	149	149	149	149	20	20
N	631	631	613	126	613	126	631	631
CFI	.960	.958	.971	.977	.970	.973	1.000	1.000
RMSEA	.252	.182	.245	.237	.176	.179	.000	.000
SRMR	.023	.027	.008	.007	.009	.012	.004	.012
Chisq (df)	164.457 (4)***	175.385 (8)***	151.677 (4)***	32.197 (4)***	159.628 (8)***	40.237 (8)***	0.354 (1)	4.203 (5)
Chisq test		10.928 (4)*			7.951 (4)$^{+}$	8.040 (4)$^{+}$		3.849 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A6

Study 1 Asian American Identity & Nonwhite Stereotypes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.823 (.023)***/ *.820*	.863 (.015)***/ *.833*	.802 (.024)***/ *.795*	.779 (.054)***/ *.783*	.846 (.016)***/ *.812*	.829 (.034)***/ *.807*	-.047 (.188)/-*.046*	-.021 (.092)/-*.029*
	W1 stereo	.016 (.023)/ *.016*	-.001 (.014)/-*.001*	.016 (.024)/ *.017*	.042 (.055)/ *.046*	.005 (.015)/ *.005*	.007 (.036)/ *.008*	.064 (.130)/ *.070*	-.038 (.049)/-*.059*
W2 stereo	W1 ID	.005 (.029)/ *.004*	.034 (.020)$^{+}$/*.032*	.006 (.030)/ *.006*	.039 (.059)/ *.039*	.040 (.021)$^{+}$/*.038*	.006 (.044)/ *.006*	-.088 (.180)/-*.074*	.017 (.082)/ *.019*
	W1 stereo	.718 (.029)***/ *.709*	.749 (.019)***/ *.721*	.688 (.030)***/ *.677*	.660 (.062)***/ *.697*	.725 (.021)***/ *.695*	.708 (.046)***/ *.731*	-.366 (.157)*/-*.348*	-.239 (.078)**/-*.293*
W3 ID	W2 ID	.890 (.020)***/ *.878*	.863 (.015)***/ *.876*	.878 (.021)***/ *.867*	.862 (.047)***/ *.839*	.846 (.016)***/ *.862*	.829 (.034)***/ *.832*	.365 (.095)***/ *.339*	-.021 (.092)/-*.011*
	W2 stereo	-.014 (.019)/-*.014*	-.001 (.014)/-*.001*	-.003 (.020)/-*.003*	-.014 (.050)/-*.014*	.005 (.015)/ *.006*	.007 (.036)/ *.007*	-.070 (.070)/-*.075*	-.038 (.049)/-*.043*
W3 stereo	W2 ID	.058 (.027)*/*.055*	.034 (.020)$^{+}$/*.034*	.070 (.029)*/*.066*	-.028 (.067)/-*.026*	.040 (.021)$^{+}$/*.040*	.006 (.044)/ *.006*	.182 (.128)/ *.141*	.017 (.082)/ *.011*
	W2 stereo	.777 (.027)***/ *.756*	.749 (.019)***/ *.754*	.760 (.029)***/ *.740*	.767 (.072)***/ *.735*	.725 (.021)***/ *.733*	.708 (.046)***/ *.705*	.020 (.102)/ *.018*	-.239 (.078)**/-*.205*

trait cov							.004 (.001)**/ *.157*	.005 (.001)***/ *.163*
W1 ID-stereo cov	.005 (.001)***/ *.147*	.005 (.001)***/ *.147*	.005 (.001)***/ *.145*	.005 (.003)/ *.121*	.005 (.001)***/ *.145*	.005 (.003)/ *.121*	.001 (.001)/ *.101*	.001 (.000)$^{+}$/*.106*
W2 ID-stereo cov	.001 (.001)*/*.092*	.001 (.001)*/*.094*	.001 (.001)$^{+}$/*.071*	.000 (.001)/ *.013*	.001 (.001)$^{+}$/*.073*	.001 (.001)*/*.082*	.000 (.001)/ *.006*	-.000 (.001)/*-.014*
W3 ID-stereo cov	.000 (.000)/ *.033*	.000 (.000)/ *.034*	.000 (.000)/ *.034*	.002 (.001)$^{+}$/*.166*	.000 (.000)/ *.036*	.000 (.001)/ *.035*	.002 (.001)$^{+}$/*.160*	.000 (.000)/ *.018*
params	17	17	149	149	149	149	20	20
N	625	625	607	125	607	125	625	625
CFI	.912	.910	.936	.944	.935	.944	1.000	.995
RMSEA	.318	.227	.322	.320	.231	.225	.000	.065
SRMR	.053	.057	.019	.018	.021	.020	.004	.036
Chisq (df)	256.202 (4)***	266.088 (8)***	255.510 (4)***	55.175 (4)***	267.067 (8)***	58.772 (8)***	0.390 (1)	18.267 (5)**
Chisq test		9.886 (4)*			11.557 (4)*	3.597 (4)		17.877 (4)**

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A7

Study 1 POC Identity & Nonwhite Stereotypes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.886 (.019)***/ *.885*	.906 (.013)***/ *.893*	.877 (.020)***/ *.873*	.860 (.050)***/ *.835*	.892 (.015)***/ *.881*	.840 (.035)***/ *.837*	.024 (.257)/ *.024*	.272 (.115)*/*.270*
	W1 stereo	.043 (.024)$^{+}$/*.033*	.021 (.017)/ *.016*	.040 (.025)/*.031*	.128 (.059)*/*.113*	.010 (.018)/ *.008*	.058 (.042)/ *.053*	.034 (.151)/ *.036*	.134 (.058)*/*.141*
W2 stereo	W1 ID	.092 (.023)***/ *.116*	.066 (.016)***/ *.082*	.072 (.025)**/ *.091*	.112 (.053)*/*.129*	.055 (.017)**/ *.067*	.106 (.040)**/ *.120*	.200 (.204)/ *.175*	.280 (.087)**/ *.293*
	W1 stereo	.686 (.029)***/ *.678*	.729 (.020)***/ *.705*	.674 (.030)***/ *.663*	.632 (.062)***/ *.668*	.720 (.021)***/ *.691*	.664 (.047)***/ *.691*	-.379 (.153)*/- *.360*	-.204 (.079)**/- *.225*
W3 ID	W2 ID	.927 (.019)***/ *.896*	.906 (.013)***/ *.890*	.907 (.021)***/ *.876*	.832 (.047)***/ *.842*	.892 (.015)***/ *.869*	.840 (.035)***/ *.825*	.321 (.131)*/*.249*	.272 (.115)*/*.249*
	W2 stereo	-.002 (.025)/-*.002*	.021 (.017)/ *.016*	-.020 (.026)/- *.015*	-.012 (.061)/-*.010*	.010 (.018)/ *.008*	.058 (.042)/ *.050*	.049 (.097)/ *.042*	.134 (.058)**/ *.116*
W3 stereo	W2 ID	.043 (.022)*/*.054*	.066 (.016)***/ *.084*	.038 (.024)/*.047*	.092 (.059)/ *.105*	.055 (.017)**/ *.068*	.106 (.040)**/ *.119*	.081 (.132)/ *.065*	.280 (.087)**/ *.265*
	W2 stereo	.768 (.028)***/ *.747*	.729 (.020)***/ *.732*	.759 (.029)***/ *.740*	.717 (.076)***/ *.687*	.720 (.021)***/ *.725*	.664 (.047)***/ *.658*	.007 (.104)/ *.007*	-.204 (.079)**/- *.183*

trait cov							.013 (.002)***/ *.328*	.012 (.002)***/ *.309*
W1 ID-stereo cov	.012 (.002)***/ *.275*	.012 (.002)***/ *.275*	.012 (.002)***/ *.268*	.017 (.004)***/ *.388*	.012 (.002)***/ *.268*	.017 (.004)***/ *.388*	.000 (.001)/ *.001*	.000 (.001)/ *.014*
W2 ID-stereo cov	.001 (.001)/ *.061*	.001 (.001)/ *.058*	.001 (.001)/*.040*	.002 (.001)+/*.171*	.001 (.001)/ *.036*	.002 (.001)+/*.165*	.002 (.001)/ *.277*	.003 (.001)**/ *.462*
W3 ID-stereo cov	.002 (.001)**/ *.111*	.002 (.001)**/ *.108*	.001 (.001)**/ *.107*	.002 (.001)+/*.158*	.001 (.001)*/*.103*	.002 (.001)+/*.150*	.001 (.001)+/*.120*	.001 (.001)*/*.143*
params	17	17	149	149	149	149	20	20
N	625	625	607	125	607	125	625	625
CFI	.929	.928	.946	.956	.945	.955	1.000	.999
RMSEA	.306	.219	.313	.293	.224	.210	.000	.033
SRMR	.050	.052	.018	.016	.019	.019	.005	.020
Chisq (df)	238.315 (4)***	247.206 (8)***	242.435 (4)***	46.981 (4)***	250.852 (8)***	51.997 (8)***	0.719 (1)	8.393 (5)
Chisq test		8.891 (4)+			8.417 (4)+	5.016 (4)		7.674 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A8

Study 1 American Identity & Nonwhite Stereotypes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.905 (.016)***/ *.915*	.926 (.011)***/ *.921*	.902 (.017)***/ *.911*	.903 (.034)***/ *.915*	.914 (.012)***/ *.917*	.923 (.023)***/ *.921*	-.081 (.198)/-*.093*	-.116 (.145)/-*.155*
	W1 stereo	.035 (.016)*/*.034*	.006 (.011)/ *.005*	.044 (.017)*/*.043*	.035 (.040)/*.033*	.016 (.012)/ *.016*	.022 (.028)/ *.020*	.224 (.090)*/*.384*	.048 (.041)/ *.108*
W2 stereo	W1 ID	-.047 (.028)$^{+}$/-*.048*	.007 (.019)/ *.007*	-.028 (.030)/-*.028*	-.022 (.052)/-*.025*	.016 (.021)/ *.016*	-.014 (.039)/-*.016*	-.532 (.269)*/-*.337*	.141 (.135)/ *.103*
	W1 stereo	.723 (.029)***/ *.715*	.754 (.019)***/ *.726*	.692 (.030)***/ *.681*	.669 (.061)***/ *.707*	.730 (.020)***/ *.699*	.709 (.046)***/ *.733*	-.277 (.161)$^{+}$/-*.263*	-.238 (.078)**/-*.291*
W3 ID	W2 ID	.946 (.015)***/ *.928*	.926 (.011)***/ *.926*	.925 (.016)***/ *.910*	.941 (.033)***/ *.912*	.914 (.012)***/ *.906*	.923 (.023)***/ *.908*	.124 (.196)/ *.099*	-.116 (.145)/-*.089*
	W2 stereo	-.020 (.015)/-*.019*	.006 (.011)/ *.006*	-.008 (.016)/-*.008*	.011 (.039)/*.009*	.016 (.012)/ *.016*	.022 (.028)/ *.019*	-.197 (.097)*/-*.287*	.048 (.041)/ *.068*
W3 stereo	W2 ID	.057 (.026)*/*.056*	.007 (.019)/ *.007*	.058 (.028)*/*.057*	-.003 (.059)/-*.003*	.016 (.021)/ *.016*	-.014 (.039)/-*.016*	.384 (.200)$^{+}$/*.190*	.141 (.135)/ *.066*
	W2 stereo	.782 (.026)***/ *.761*	.754 (.019)***/ *.759*	.764 (.028)***/ *.744*	.763 (.071)***/ *.731*	.730 (.020)***/ *.737*	.709 (.046)***/ *.706*	.112 (.103)/ *.100*	-.238 (.078)**/-*.204*

trait cov							.003 (.001)*/*.087*	.002 (.001)/ *.069*
W1 ID-stereo cov	.003 (.001)*/*.094*	.003 (.001)*/*.094*	.003 (.001)*/*.093*	.005 (.004)/*.115*	.003 (.001)*/*.093*	.005 (.004)/ *.115*	.001 (.001)/ *.145*	.000 (.000)/ *.054*
W2 ID-stereo cov	.000 (.000)/ *.024*	.000 (.000)/ *.024*	.000 (.000)/ *.014*	.001 (.001)/*.082*	.000 (.000)/ *.012*	.001 (.001)/ *.080*	-.001 (.001)/-*.146*	.001 (.001)/ *.242*
W3 ID-stereo cov	.000 (.000)/ *.051*	.000 (.000)/ *.052*	.001 (.000)/ *.058*	.001 (.001)/*.127*	.001 (.000)/ *.056*	.001 (.001)/ *.126*	.001 (.000)/ *.098*	.000 (.000)/ *.066*
params	17	17	149	149	149	149	20	20
N	625	625	607	125	607	125	625	625
CFI	.921	.917	.941	.943	.939	.945	1.000	.997
RMSEA	.341	.248	.341	.360	.245	.250	.000	.063
SRMR	.050	.056	.018	.016	.020	.018	.001	.032
Chisq (df)	295.514 (4)***	314.579 (8)***	286.584 (4)***	68.769 (4)***	300.154 (8)***	70.706 (8)***	0.017 (1)	17.445 (5)**
Chisq test		19.065 (4)***			13.570 (4)**	1.937 (4)		17.428 (4)**

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A9

Study 1 Asian American Identity & White FT Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.828 (.023)***/ _.826_	.859 (.015)***/ _.834_	.806 (.024)***/ _.801_	.795 (.053)***/ _.799_	.842 (.015)***/ _.812_	.830 (.035)***/ _.812_	.041 (.166)/ _.041_	-.044 (.092)/-_.062_
	W1 FT	-.064 (.020)**/-_.072_	-.007 (.013)/-_.007_	-.043 (.021)*/-_.049_	.006 (.047)/_.007_	.000 (.014)/ _.000_	.025 (.032)/ _.028_	-.256 (.095)**/-_.332_	-.036 (.058)/-_.060_
W2 FT	W1 ID	.067 (.030)*/_.058_	.011 (.021)/ _.010_	.061 (.031)$^+$/_.052_	.066 (.063)/_.060_	.014 (.022)/ _.013_	-.027 (.046)/-_.026_	.354 (.179)*/_.239_	-.052 (.108)/-_.039_
	W1 FT	.790 (.026)***/ _.765_	.781 (.019)***/ _.763_	.801 (.028)***/ _.774_	.761 (.056)***/ _.779_	.775 (.020)***/ _.764_	.708 (.042)***/ _.754_	.150 (.136)/ _.133_	.150 (.091)$^+$/_.133_
W3 ID	W2 ID	.883 (.019)***/ _.873_	.859 (.015)***/ _.874_	.871 (.021)***/ _.863_	.853 (.047)***/ _.831_	.842 (.015)***/ _.862_	.830 (.035)***/ _.830_	.364 (.091)***/ _.343_	-.044 (.092)/-_.038_
	W2 FT	.033 (.017)*/_.038_	-.007 (.013)/-_.008_	.030 (.017)$^+$/_.035_	.038 (.042)/_.040_	.000 (.014)/ _.000_	.025 (.032)/ _.026_	.135 (.059)*/_.186_	-.036 (.058)/-_.060_
W3 FT	W2 ID	-.049 (.030)/-_.042_	.011 (.021)/ _.010_	-.037 (.032)/-_.032_	-.128 (.067)$^+$/-_.116_	.014 (.022)/ _.013_	-.027 (.046)/-_.025_	-.254 (.123)*/-_.172_	-.052 (.108)/-_.028_
	W2 FT	.768 (.026)***/ _.767_	.781 (.019)***/ _.767_	.747 (.027)***/ _.744_	.654 (.059)***/ _.658_	.775 (.020)***/ _.747_	.708 (.042)***/ _.670_	.220 (.088)**/ _.218_	.150 (.091)$^+$/_.155_

trait cov							.001 (.001)/ _.035_	.001 (.001)/ _.030_
W1 ID-FT cov	.001 (.002)/ _.033_	.001 (.002)/ _.033_	.001 (.002)/ _.028_	.003 (.004)/_.083_	.001 (.002)/ _.028_	.003 (.004)/ _.083_	.000 (.001)/ _.028_	.001 (.001)$^{+}$/_.117_
W2 ID-FT cov	.001 (.001)*/_.084_	.001 (.001)$^{+}$/_.077_	.001 (.001)*/_.083_	.001 (.001)/_.115_	.001 (.001)$^{+}$/_.075_	.001 (.001)/ _.101_	.001 (.001)/ _.123_	-.000 (.001)/-_.028_
W3 ID-FT cov	.000 (.000)/ _.023_	.000 (.001)/ _.016_	.000 (.000)/ _.023_	.002 (.001)/_.137_	.000 (.000)/ _.015_	.001 (.001)/ _.126_	.000 (.001)/ _.028_	-.000 (.000)/-_.023_
params	17	17	149	149	149	149	20	20
N	627	627	609	124	609	124	627	627
CFI	.937	.929	.956	.954	.952	.949	1.000	.993
RMSEA	.272	.204	.269	.284	.199	.213	.000	.079
SRMR	.041	.050	.015	.015	.017	.020	.001	.036
Chisq (df)	189.526 (4)***	216.167 (8)***	180.542 (4)***	44.132 (4)***	201.413 (8)***	52.805 (8)***	0.033 (1)	24.351 (5)***
Chisq test		26.641 (4)***			20.871 (4)***	8.673 (4)$^{+}$		24.318 (4)***

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/_standardized coefficient_.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A10

Study 1 POC Identity & White FT Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.888 (.018)***/ *.889*	.902 (.013)***/ *.891*	.873 (.020)***/ *.870*	.877 (.051)***/ *.855*	.886 (.015)***/ *.875*	.834 (.034)***/ *.823*	.014 (.214)/ *.014*	.049 (.144)/ *.058*
	W1 FT	-.028 (.021)/-*.024*	-.033 (.015)*/- *.028*	-.028 (.022)/-*.024*	.001 (.051)/*.001*	-.034 (.016)*/- *.029*	-.090 (.036)*/- *.085*	.141 (.129)/ *.170*	.138 (.067)*/*.187*
W2 FT	W1 ID	-.020 (.023)/-*.022*	-.039 (.016)*/- *.044*	-.025 (.026)/-*.028*	-.032 (.056)/- *.035*	-.034 (.018)$^{+}$/- *.038*	-.086 (.040)*/- *.095*	.152 (.222)/ *.114*	.026 (.116)/ *.020*
	W1 FT	.788 (.027)***/ *.764*	.773 (.019)***/ *.754*	.803 (.028)***/ *.776*	.761 (.056)***/ *.778*	.771 (.020)***/ *.760*	.691 (.042)***/ *.733*	-.010 (.175)/-*.009*	.118 (.093)/ *.105*
W3 ID	W2 ID	.918 (.019)***/ *.887*	.902 (.013)***/ *.886*	.900 (.021)***/ *.869*	.803 (.043)***/ *.810*	.886 (.015)***/ *.866*	.834 (.034)***/ *.827*	.202 (.164)/ *.157*	.049 (.144)/ *.038*
	W2 FT	-.039 (.021)$^{+}$/- *.034*	-.033 (.015)*/- *.028*	-.040 (.022)$^{+}$/- *.034*	-.164 (.046)***/- *.150*	-.034 (.016)*/- *.029*	-.090 (.036)*/- *.080*	.115 (.099)/ *.127*	.138 (.067)*/*.165*
W3 FT	W2 ID	-.058 (.023)*/- *.064*	-.039 (.016)*/- *.044*	-.041 (.026)/-*.046*	-.138 (.056)*/- *.153*	-.034 (.018)$^{+}$/- *.037*	-.086 (.040)*/- *.091*	-.149 (.140)/-*.102*	.026 (.116)/ *.018*

W2 FT	.759 (.026)***/ *.757*	.773 (.019)***/ *.762*	.741 (.027)***/ *.737*	.613 (.059)***/ *.617*	.771 (.020)***/ *.745*	.691 (.042)***/ *.653*	.178 (.092)$^{+}$/ *.171*	.118 (.093)/ *.121*
trait cov							-.009 (.002)***/ -*.212*	-.009 (.002)***/ -*.215*
W1 ID-FT cov	-.008 (.002)***/ -*.160*	-.008 (.002)***/ -*.160*	-.008 (.002)***/ -*.165*	-.009 (.004)*/ -*.200*	-.008 (.002)***/ -*.165*	-.009 (.004)*/ -*.200*	.001 (.001)/ *.152*	.000 (.001)/ *.054*
W2 ID-FT cov	.001 (.001)*/*.087*	.001 (.001)*/*.086*	.001 (.001)*/*.080*	-.001 (.001)/-*.053*	.001 (.001)*/*.080*	-.000 (.001)/-*.031*	.003 (.002)$^{+}$/*.305*	.003 (.001)*/*.314*
W3 ID-FT cov	.002 (.001)*/*.102*	.002 (.001)*/*.101*	.002 (.001)**/ *.109*	-.000 (.001)/-*.031*	.002 (.001)**/ *.110*	-.000 (.001)/-*.011*	.001 (.001)/ *.083*	.001 (.001)*/*.142*
params	17	17	149	149	149	149	20	20
N	627	627	609	124	609	124	627	627
CFI	.945	.945	.960	.963	.960	.956	.999	1.000
RMSEA	.269	.190	.271	.262	.191	.203	.066	.023
SRMR	.039	.040	.014	.013	.015	.017	.013	.016
Chisq (df)	185.327 (4)***	188.901 (8)***	182.388 (4)***	38.033 (4)***	186.150 (8)***	48.995 (8)***	3.728 (1)$^{+}$	6.651 (5)
Chisq test		3.574 (4)			3.762 (4)	10.962 (4)*		2.923 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.
Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A11

Study 1 American Identity & White FT Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.904 (.017)***/ *.917*	.918 (.012)***/ *.914*	.901 (.018)***/ *.912*	.897 (.036)***/ *.913*	.907 (.012)***/ *.912*	.914 (.025)***/ *.917*	-.077 (.200)/-*.092*	-.065 (.145)/-*.084*
	W1 FT	.006 (.016)/ *.006*	.020 (.011)$^+$/*.021*	.015 (.016)/ *.016*	.011 (.037)/ *.011*	.022 (.011)*/*.023*	.016 (.026)/ *.015*	-.077 (.066)/-*.161*	-.041 (.046)/-*.092*
W2 FT	W1 ID	.137 (.030)***/ *.125*	.110 (.021)***/ *.101*	.145 (.032)***/ *.131*	.119 (.057)*/*.128*	.108 (.023)***/ *.101*	.077 (.042)$^+$/*.087*	.457 (.326)/ *.230*	-.111 (.164)/-*.061*
	W1 FT	.743 (.028)***/ *.720*	.740 (.020)***/ *.725*	.763 (.029)***/ *.737*	.723 (.058)***/ *.740*	.742 (.020)***/ *.734*	.678 (.044)***/ *.725*	.089 (.130)/ *.078*	.065 (.094)/ *.063*
W3 ID	W2 ID	.931 (.016)***/ *.915*	.918 (.012)***/ *.920*	.912 (.017)***/ *.899*	.928 (.035)***/ *.904*	.907 (.012)***/ *.901*	.914 (.025)***/ *.903*	.052 (.212)/ *.041*	-.065 (.145)/-*.053*
	W2 FT	.031 (.015)*/*.034*	.020 (.011)$^+$/*.021*	.027 (.015)$^+$/*.030*	.018 (.035)/ *.017*	.022 (.011)*/*.023*	.016 (.026)/ *.014*	.114 (.082)/ *.213*	-.041 (.046)/-*.079*
W3 FT	W2 ID	.080 (.031)**/ *.072*	.110 (.021)***/ *.100*	.069 (.033)*/*.062*	.027 (.064)/ *.028*	.108 (.023)***/ *.096*	.077 (.042)$^+$/*.081*	-.226 (.239)/-*.095*	-.111 (.164)/-*.046*
	W2 FT	.738 (.028)***/ *.737*	.740 (.020)***/ *.726*	.723 (.028)***/ *.720*	.625 (.065)***/ *.630*	.742 (.020)***/ *.713*	.678 (.044)***/ *.635*	.181 (.100)$^+$/*.180*	.065 (.094)/ *.064*

trait cov							.015 (.002)***/ *.445*	.016 (.002)***/ *.457*
W1 ID-FT cov	.015 (.002)***/ *.380*	.015 (.002)***/ *.380*	.016 (.002)***/ *.386*	.020 (.005)***/ *.425*	.016 (.002)***/ *.386*	.020 (.005)***/ *.425*	.000 (.001)/ *.067*	.000 (.000)/ *.068*
W2 ID-FT cov	.001 (.000)*/*.098*	.001 (.000)*/*.096*	.001 (.000)*/*.086*	.002 (.001)*/*.190*	.001 (.000)*/*.084*	.002 (.001)*/*.183*	.001 (.001)/ *.266*	-.000 (.001)/-*.074*
W3 ID-FT cov	.001 (.000)*/*.086*	.001 (.000)*/*.084*	.001 (.000)+/*.073*	.002 (.001)+/*.173*	.001 (.000)+/*.071*	.002 (.001)+/*.166*	.000 (.001)/ *.067*	.000 (.000)/ *.046*
params	17	17	149	149	149	149	20	20
N	627	627	609	124	609	124	627	987
CFI	.944	.944	.960	.960	.959	.959	1.000	1.000
RMSEA	.293	.208	.285	.302	.203	.216	.000	.007
SRMR	.038	.040	.013	.013	.015	.017	.002	.016
Chisq (df)	218.639 (4)***	225.689 (8)***	201.496 (4)***	49.169 (4)***	208.112 (8)***	54.238 (8)***	0.110 (1)	5.156 (5)
Chisq test		7.050 (4)			6.616 (4)	5.069 (4)		5.046 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A12

Study 1 Asian American Identity & White Stereotypes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.828 (.023)***/ *.824*	.861 (.015)***/ *.833*	.805 (.024)***/ *.798*	.780 (.053)***/ *.783*	.845 (.015)***/ *.812*	.828 (.034)***/ *.806*	-.056 (.191)/-*.054*	.041 (.093)/ *.051*
	W1 stereo	-.045 (.024)$^{+}$/-*.043*	-.004 (.015)/-*.004*	-.028 (.024)/-*.027*	.038 (.054)/*.038*	.001 (.015)/ *.001*	.012 (.037)/ *.011*	-.152 (.076)*/-*.217*	-.136 (.039)**/-*.231*
W2 stereo	W1 ID	.027 (.032)/*.028*	.028 (.021)/ *.028*	.041 (.033)/*.041*	-.024 (.058)/-*.027*	.041 (.022)$^{+}$/*.041*	.020 (.043)/ *.022*	-.031 (.212)/-*.019*	-.242 (.088)**/-*.171*
	W1 stereo	.609 (.033)***/ *.589*	.640 (.022)***/ *.608*	.605 (.034)***/ *.583*	.599 (.059)***/ *.685*	.631 (.022)***/ *.599*	.627 (.045)***/ *.700*	.024 (.110)/ *.022*	.148 (.070)*/*.142*
W3 ID	W2 ID	.886 (.019)***/ *.875*	.861 (.015)***/ *.876*	.876 (.021)***/ *.867*	.861 (.046)***/ *.838*	.845 (.015)***/ *.864*	.828 (.034)***/ *.830*	.358 (.093)***/ *.333*	.041 (.093)/ *.038*
	W2 stereo	.024 (.020)/*.023*	-.004 (.015)/-*.004*	.021 (.020)/*.021*	-.014 (.052)/-*.012*	.001 (.015)/ *.001*	.012 (.037)/ *.010*	.003 (.056)/ *.004*	-.136 (.039)**/-*.230*
W3 stereo	W2 ID	.029 (.029)/*.029*	.028 (.021)/ *.030*	.041 (.030)/*.042*	.069 (.064)/*.073*	.041 (.022)$^{+}$/*.044*	.020 (.043)/ *.022*	-.082 (.108)/-*.053*	-.242 (.088)**/-*.142*

W2 stereo	.665 (.030)***/ *.661*	.640 (.022)***/ *.653*	.651 (.030)***/ *.653*	.678 (.073)***/ *.638*	.631 (.022)***/ *.646*	.627 (.045)***/ *.618*	.227 (.072)**/ *.225*	.148 (.070)*/*.155*
trait cov							.002 (.001)$^{+}$/*.098*	.003 (.001)**/ *.134*
W1 ID-stereo cov	.002 (.001)/*.060*	.002 (.001)/ *.060*	.002 (.001)/*.056*	.004 (.003)/*.109*	.002 (.001)/ *.056*	.004 (.003)/ *.109*	-.000 (.001)/-*.022*	.000 (.001)/ *.045*
W2 ID-stereo cov	.000 (.001)/*.016*	.000 (.001)/ *.019*	.000 (.001)/*.016*	.001 (.001)/*.104*	.000 (.001)/ *.018*	.001 (.001)/ *.104*	-.001 (.001)/-*.117*	-.003 (.001)**/-*.356*
W3 ID-stereo cov	-.000 (.000)/-*.003*	-.000 (.000)/-*.001*	-.000 (.000)/-*.013*	.000 (.001)/*.025*	-.000 (.000)/-*.011*	.000 (.001)/ *.027*	-.000 (.001)/-*.012*	-.001 (.001)/-*.072*
params	17	17	149	149	149	149	20	20
N	632	632	614	126	614	126	632	632
CFI	.939	.936	.959	.967	.958	.967	1.000	.996
RMSEA	.242	.175	.240	.232	.172	.163	.000	.054
SRMR	.048	.051	.017	.014	.018	.018	.004	.033
Chisq (df)	152.156 (4)***	162.833 (8)***	145.023 (4)***	31.128 (4)***	154.047 (8)***	34.773 (8)***	0.257 (1)	14.349 (5)*
Chisq test		10.677 (4)*			9.024 (4)$^{+}$	3.645 (4)		14.092 (4)**

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A13

Study 1 POC Identity & White Stereotypes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.892 (.018)***/ *.893*	.908 (.013)***/ *.897*	.877 (.020)***/ *.875*	.886 (.049)***/ *.864*	.891 (.014)***/ *.880*	.850 (.033)***/ *.846*	.060 (.221)/ *.061*	.180 (.147)/ *.194*
	W1 stereo	-.025 (.025)/-*.018*	-.009 (.017)/-*.006*	-.020 (.025)/-*.014*	-.038 (.056)/-*.031*	-.007 (.018)/-*.005*	-.079 (.040)*/-*.067*	.003 (.083)/ *.004*	.071 (.051)/ *.099*
W2 stereo	W1 ID	-.010 (.024)/-*.013*	-.001 (.016)/-*.001*	-.001 (.027)/-*.002*	-.045 (.050)/-*.061*	.003 (.018)/ *.004*	.010 (.037)/ *.013*	.038 (.229)/ *.026*	.095 (.104)/ *.067*
	W1 stereo	.610 (.033)***/ *.590*	.641 (.022)***/ *.609*	.608 (.034)***/ *.586*	.594 (.058)***/ *.679*	.634 (.022)***/ *.602*	.633 (.045)***/ *.705*	-.015 (.114)/-*.014*	.198 (.070)**/ *.152*
W3 ID	W2 ID	.924 (.019)***/ *.893*	.908 (.013)***/ *.892*	.905 (.021)***/ *.875*	.821 (.043)***/ *.832*	.891 (.014)***/ *.871*	.850 (.033)***/ *.842*	.273 (.141)$^{+}$/*.218*	.180 (.147)/ *.161*
	W2 stereo	.007 (.025)/*.005*	-.009 (.017)/-*.007*	.006 (.025)/*.004*	-.125 (.058)*/-*.091*	-.007 (.018)/-*.005*	-.079 (.040)*/-*.060*	.084 (.082)/ *.098*	.071 (.051)/ *.097*
W3 stereo	W2 ID	.006 (.023)/*.008*	-.001 (.016)/-*.001*	.006 (.025)/*.018*	.074 (.053)/*.096*	.003 (.018)/ *.004*	.010 (.037)/ *.013*	.069 (.114)/ *.046*	.095 (.104)/ *.068*
	W2 stereo	.666 (.030)***/ *.663*	.641 (.022)***/ *.654*	.654 (.030)***/ *.655*	.697 (.072)***/ *.656*	.634 (.022)***/ *.648*	.633 (.045)***/ *.623*	.221 (.073)**/ *.216*	.198 (.070)**/ *.216*

trait cov							-.003 (.002)$^{+}$/-*.099*	-.003 (.002)*/-*.115*
W1 ID-stereo cov	-.003 (.002)*/ -*.081*	-.003 (.002)*/ -*.081*	-.003 (.002)*/ -*.081*	.000 (.004)/*.000*	-.003 (.002)*/ -*.081*	.000 (.004)/ *.000*	.000 (.001)/ *.030*	.001 (.001)/ *.090*
W2 ID-stereo cov	.000 (.001)/*.021*	.000 (.001)/ *.023*	.000 (.001)/*.013*	.000 (.001)/*.006*	.000 (.001)/ *.013*	-.000 (.001)/-*.004*	.001 (.002)/ *.060*	.001 (.001)/ *.107*
W3 ID-stereo cov	.000 (.001)/*.015*	.000 (.001)/ *.016*	.000 (.001)/*.007*	.000 (.001)/*.020*	.000 (.001)/ *.008*	.000 (.001)/ *.009*	.001 (.001)/ *.083*	.001 (.001)/ *.083*
params	17	17	149	149	149	149	20	20
N	632	632	614	126	614	126	632	632
CFI	.950	.950	.965	.975	.965	.973	.999	.997
RMSEA	.235	.166	.235	.208	.165	.153	.054	.049
SRMR	.045	.046	.016	.013	.017	.017	.014	.028
Chisq (df)	143.992 (4)***	147.894 (8)***	139.859 (4)***	25.899 (4)***	142.252 (8)***	31.580 (8)***	2.874 (1)$^{+}$	12.616 (5)*
Chisq test		3.902 (4)			2.393 (4)	5.681 (4)		9.742 (4)*

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A14

Study 1 American Identity & White Stereotypes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.910 (.016)***/ *.921*	.923 (.011)***/ *.919*	.908 (.017)***/ *.918*	.900 (.035)***/ *.916*	.912 (.012)***/ *.916*	.912 (.024)***/ *.912*	-.169 (.217)/-*.198*	-.042 (.138)/-*.052*
	W1 stereo	-.008 (.018)/-*.007*	.011 (.012)/ *.010*	-.004 (.018)/-*.003*	.005 (.040)/ *.004*	.011 (.012)/ *.010*	.045 (.029)/ *.039*	-.057 (.046)/-*.140*	-.082 (.031)**/- *.202*
W2 stereo	W1 ID	.098 (.031)**/ *.106*	.102 (.021)***/ *.108*	.095 (.034)**/ *.101*	.034 (.051)/ *.045*	.095 (.023)***/ *.100*	.088 (.038)*/*.113*	-.177 (.403)/-*.079*	-.400 (.136)**/- *.188*
	W1 stereo	.581 (.034)***/ *.562*	.611 (.023)***/ *.580*	.585 (.035)***/ *.564*	.586 (.060)***/ *.670*	.611 (.023)***/ *.580*	.605 (.046)***/ *.671*	.055 (.102)/ *.052*	.159 (.070)*/*.150*
W3 ID	W2 ID	.937 (.016)***/ *.921*	.923 (.011)***/ *.925*	.917 (.017)***/ *.904*	.927 (.032)***/ *.900*	.912 (.012)***/ *.905*	.912 (.024)***/ *.901*	.051 (.223)/ *.039*	-.042 (.138)/-*.035*
	W2 stereo	.028 (.017)$^{+}$/*.026*	.011 (.012)/ *.010*	.025 (.017)/ *.023*	.093 (.041)*/*.069*	.011 (.012)/ *.011*	.045 (.029)/ *.035*	-.032 (.080)/-*.064*	-.082 (.031)**/- *.177*
W3 stereo	W2 ID	.107 (.029)***/ *.113*	.102 (.021)***/ *.111*	.097 (.031)**/ *.102*	.156 (.056)**/ *.192*	.095 (.023)***/ *.102*	.088 (.038)*/*.112*	-.321 (.214)/-*.123*	-.400 (.136)**/- *.162*

W2 stereo	.637 (.031)***/ *.634*	.611 (.023)***/ *.625*	.633 (.031)***/ *.634*	.652 (.071)***/ *.614*	.611 (.023)***/ *.626*	.605 (.046)***/ *.601*	.210 (.083)*/*.210*	.159 (.070)*/*.167*
trait cov							.010 (.001)***/ *.382*	.010 (.001)***/ *.404*
W1 ID-stereo cov	.009 (.001)***/ *.276*	.009 (.001)***/ *.276*	.009 (.001)***/ *.275*	.012 (.004)**/ *.290*	.009 (.001)***/ *.275*	.012 (.004)**/ *.290*	.000 (.001)/ *.043*	.000 (.000)/ *.025*
W2 ID-stereo cov	.000 (.000)/ *.041*	.000 (.000)/ *.043*	.000 (.000)/ *.028*	-.000 (.001)/-*.045*	.000 (.000)/ *.029*	-.000 (.001)/-*.036*	-.001 (.001)/-*.191*	-.002 (.001)**/-*.324*
W3 ID-stereo cov	.001 (.000)*/*.080*	.001 (.000)*/*.082*	.001 (.000)*/*.080*	.001 (.001)/ *.067*	.001 (.000)*/*.081*	.001 (.001)/ *.079*	.000 (.000)/ *.023*	.000 (.000)/ *.006*
params	17	17	149	149	149	149	20	20
N	632	632	614	126	614	126	632	632
CFI	.946	.945	.962	.974	.963	.971	1.000	1.000
RMSEA	.266	.189	.258	.234	.181	.174	.026	.012
SRMR	.043	.045	.016	.010	.016	.017	.011	.020
Chisq (df)	182.566 (4)***	188.964 (8)***	166.947 (4)***	31.697 (4)***	169.690 (8)***	38.522 (8)***	1.427 (1)	5.476 (5)
Chisq test		6.398 (4)			2.743 (4)	6.825 (4)		5.049 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A15

Study 1 Asian American Identity & Immigration Attitudes Panel Model Results

		CLPM Model 1[a]	**CLPM Model 1, stationarity**[b]	**CLPM Model 2**[c]	**CLPM Model 3**[d]	**CLPM Model 2, stationarity**[e]	**CLPM Model 3, stationarity**[f]	**RI-CLPM**[g]	**RI-CLPM, stationarity**[h]
W2 ID	W1 ID	.820 (.023)***/ *.817*	.859 (.015)***/ *.830*	.802 (.024)***/ *.795*	.792 (.054)***/ *.794*	.843 (.015)***/ *.809*	.818 (.034)***/ *.798*	-.051 (.127)/-*.049*	-.037 (.088)/ -*.053*
	W1 Immig	.037 (.021)$^{+}$/*.040*	.015 (.014)/ *.016*	.009 (.029)/*.009*	-.051 (.061)/-*.057*	.024 (.019)/ *.025*	.034 (.039)/ *.037*	3.338 (2.304)/ *.630*	-.455 (.310)/ -*.089*
W2 Immig	W1 ID	-.005 (.006)/-*.005*	.001 (.004)/ *.001*	-.004 (.006)/-*.004*	-.001 (.014)/-*.001*	.001 (.004)/ *.001*	.012 (.009)/ *.011*	-.032 (.042)/-*.114*	-.034 (.021)$^{+}$/-*.118*
	W1 Immig	.994 (.006)***/ *.991*	.990 (.004)***/ *.990*	.986 (.008)***/ *.982*	1.001 (.016)***/ *.992*	.981 (.005)***/ *.979*	.978 (.010)***/ *.980*	-.286 (1.146)/-*.196*	-.038 (.103)/ -*.018*
W3 ID	W2 ID	.887 (.020)***/ *.876*	.859 (.015)***/ *.873*	.873 (.021)***/ *.865*	.854 (.045)***/ *.834*	.843 (.015)***/ *.862*	.818 (.034)***/ *.826*	.378 (.101)***/ *.354*	-.037 (.088)/ -*.032*
	W2 Immig	-.001 (.018)/-*.001*	.015 (.014)/ *.016*	.036 (.024)/*.039*	.082 (.050)/ *.090*	.024 (.019)/ *.026*	.034 (.039)/ *.037*	-.191 (.296)/-*.049*	-.455 (.310)/ -*.161*
W3 Immig	W2 ID	.005 (.005)/ *.005*	.001 (.004)/ *.001*	.005 (.006)/*.005*	.023 (.012)$^{+}$/b*.021*	.001 (.004)/ *.001*	.012 (.009)/ *.011*	.145 (.168)/ *1.107*	-.034 (.021)$^{+}$

W2 Immig	.987 (.005)***/ *.992*	.990 (.004)***/ *.992*	.977 (.007)***/ *.983*	.968 (.013)***/ *.977*	.981 (.005)***/ *.985*	.978 (.010)***/ *.981*	-.242 (.516)/-*.510*	-.038 (.103)
trait cov							.005 (.001)**/ *.142*	.005 (.001)***/ *.151*
W1 ID-Immig cov	.005 (.001)**/ *.132*	.005 (.001)**/ *.132*	.005 (.001)**/ *.134*	.005 (.004)/ *.122*	.005 (.001)**/ *.134*	.005 (.004)/ *.122*	.000 (.000)/ *.022*	.000 (.000)/ *.080*
W2 ID-Immig cov	.000 (.000)/ *.029*	.000 (.000)/ *.032*	.000 (.000)/*.027*	-.001 (.000)**/ -*.252*	.000 (.000)/ *.028*	-.001 (.000)**/ -*.258*	.001 (.000)*/*.646*	-.000 (.000)/ -*.213*
W3 ID-Immig cov	.000 (.000)/ *.037*	.000 (.000)/ *.039*	.000 (.000)/*.049*	.000 (.000)/ *.045*	.000 (.000)/ *.050*	.000 (.000)/ *.045*	.000 (.000)/ *.227*	-.000 (.000)/ -*.032*
params	17	17	149	149	149	149	20	20
N	630	630	612	124	612	124	630	630
CFI	.812	.811	.839	.841	.839	.839	1.000	.999
RMSEA	.787	.557	.790	.808	.560	.574	.000	.048
SRMR	.021	.026	.008	.007	.010	.013	.002	.026
Chisq (df)	1565.120 (4)***	1573.103 (8)***	1533.409 (4)***	327.692 (4)***	1541.115 (8)***	335.100 (8)***	0.103 (1)	12.244 (5)*
Chisq test		7.983 (4)$^{+}$			7.706 (4)	7.408 (4)		12.141 (4)*

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

[a] Starting values from OLS.
[b] Starting values from failed CLPM w/ stationarity (W1-W2 estimates).
[c] Starting values from OLS (all coefficients, both time lags)
[d] Starting values from OLS (all coefficients, both time lags).
[e] Starting values from failed CLPM w/ stationarity (a1, b1, a2, & b2, both time lags).
[f] Starting values from failed CLPM w/ stationarity (a1, b1, a2, & b2, both time lags).
[g] Negative variance (cimmig_w3 var = -.000, SE = .000, n.s.). No longer converges if fix negative variance to 0.
[h] Negative variance (cimmig_w3 var = -.000, SE = .000, n.s.). If fix negative variance to 0, warning that covariance matrix of latent variables is not positive definite. Estimates from model with negative variance (to be comparable to model without stationarity).

Table A16

Study 1 POC Identity & Immigration Attitudes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2[a]**	**CLPM Model 3**	**CLPM Model 2, stationarity[b]**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity[c]**
W2 ID	W1 ID	.883 (.019)***/ *.884*	.898 (.014)***/ *.887*	.876 (.020)***/ *.873*	.882 (.049)***/ *.861*	.889 (.015)***/ *.879*	.852 (.033)***/ *.849*	-.096 (.205)/-*.095*	.324 (.113)**/ *.302*
	W1 Immig	.034 (.023)/ *.028*	.033 (.017)*/*.027*	.014 (.030)/ *.012*	.034 (.064)/*.031*	.013 (.021)/ *.011*	.030 (.043)/ *.028*	-2.719 (3.040)/-*.509*	-.136 (.211)/-*.013*
W2 Immig	W1 ID	.004 (.005)/ *.004*	.007 (.003)*/*.008*	.002 (.005)/ *.003*	.000 (.012)/*.000*	.005 (.003)/ *.007*	.006 (.008)/ *.006*	.005 (.055)/*.020*	-.000 (.010)/-*.001*
	W1 Immig	.991 (.006)***/ *.988*	.987 (.004)***/ *.987*	.985 (.008)***/ *.980*	1.001 (.016)***/ *.992*	.980 (.005)***/ *.978*	.981 (.010)***/ *.982*	-.401 (1.187)/-*.272*	.082 (.091)/ *.028*
W3 ID	W2 ID	.916 (.020)***/ *.885*	.898 (.014)***/ *.883*	.905 (.021)***/ *.874*	.832 (.044)***/ *.841*	.889 (.015)***/ *.870*	.852 (.033)***/ *.844*	.268 (.169)/*.197*	.324 (.113)**/ *.310*
	W2 Immig	.031 (.024)/ *.025*	.033 (.017)*/*.026*	.011 (.031)/ *.008*	.016 (.058)/*.015*	.013 (.021)/ *.011*	.030 (.043)/ *.028*	-.237 (.501)/-*.048*	-.136 (.211)/-*.037*
W3 Immig	W2 ID	.009 (.004)*/*.011*	.007 (.003)*/*.008*	.008 (.005)$^{+}$/*.010*	.008 (.010)/*.009*	.005 (.003)/ *.007*	.006 (.008)/ *.006*	-.140 (.214)/-*1.128*	-.000 (.010)
	W2 Immig	.984 (.005)***/ *.988*	.987 (.004)***/ *.989*	.976 (.007)***/ *.982*	.968 (.013)***/ *.977*	.980 (.005)***/ *.984*	.981 (.010)***/ *.983*	-.348 (.653)/-*.772*	.082 (.091)

trait cov							.018 (.002)***/ *.391*	.017 (.002)***/ *.391*
W1 ID-Immig cov	.018 (.002)***/ *.375*	.018 (.002)***/ *.375*	.018 (.002)***/ *.374*	.016 (.005)***/ *.332*	.018 (.002)***/ *.374*	.016 (.005)***/ *.332*	-.000 (.000)/-*.014*	-.000 (.000)/-*.074*
W2 ID-Immig cov	-.000 (.000)*/-*.094*	-.000 (.000)*/-*.093*	-.000 (.000)*/-*.092*	-.000 (.000)/-*.124*	-.000 (.000)*/-*.092*	-.000 (.000)/-*.124*	-.001 (.000)*/ -*.775*	-.000 (.000)$^{+}$/-*.107*
W3 ID-Immig cov	.000 (.000)/ *.012*	.000 (.000)/ *.013*	.000 (.000)/ *.013*	.000 (.000)/*.050*	.000 (.000)/ *.014*	.000 (.000)/ *.051*	.000 (.000)/*.994*	.000 (.000)/ *.273*
params	17	17	149	149	149	149	20	20
N	630	630	612	124	612	124	630	630
CFI	.824	.824	.848	.847	.848	.847	1.000	1.000
RMSEA	.783	.553	.787	.800	.556	.565	.000	.022
SRMR	.014	.017	.005	.005	.006	.007	.006	.012
Chisq (df)	1547.994 (4)***	1550.767 (8)***	1520.744 (4)***	321.548 (4)***	1523.004 (8)***	324.771 (8)***	0.910 (1)	6.471 (5)
Chisq test		2.773 (4)			2.260 (4)	3.223 (4)	1547.084 (3)***	5.561 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.
Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

[a] Starting values from OLS (all coefficients, W1-W2).
[b] Starting values from failed CLPM w/ stationarity (a1, b1, a2, & b2, both time lags).
[c] Negative variance (cimmig_w3 var = -.000, SE = .000, n.s.). No longer converges if fix negative variance to 0.

Table A17

Study 1 American Identity & Immigration Attitudes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity[a]**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity[b]**
W2 ID	W1 ID	.904 (.016)***/ *.914*	.922 (.011)***/ *.917*	.906 (.017)***/ *.915*	.902 (.034)***/ *.915*	.914 (.012)***/ *.919*	.918 (.023)***/ *.921*	-.112 (.206)/-*.135*	-.067 (.131)/ -*.086*
	W1 Immig	-.025 (.015)/-*.025*	-.023 (.011)*/-*.024*	-.041 (.020)*/-*.043*	-.044 (.044)/-*.042*	-.017 (.014)/-*.017*	-.022 (.030)/-*.021*	.940 (3.733)/*.225*	-.242 (.283)/ -*.047*
W2 Immig	W1 ID	-.005 (.006)/-*.005*	-.002 (.004)/-*.002*	-.005 (.006)/-*.005*	.000 (.012)/*.000*	-.001 (.004)/-*.001*	.005 (.008)/ *.005*	.009 (.071)/ *.025*	-.033 (.036)/ -*.072*
	W1 Immig	.992 (.006)***/ *.989*	.990 (.004)***/ *.990*	.985 (.008)***/ *.981*	1.001 (.016)***/ *.992*	.981 (.005)***/ *.979*	.982 (.010)***/ *.983*	-1.103 (1.006)/-*.663*	.072 (.097)/ *.024*
W3 ID	W2 ID	.938 (.015)***/ *.923*	.922 (.011)***/ *.923*	.922 (.016)***/ *.909*	.938 (.033)***/ *.913*	.914 (.012)***/ *.907*	.918 (.023)***/ *.908*	.018 (.231)/ *.015*	-.067 (.131)/ -*.055*
	W2 Immig	-.022 (.015)/-*.022*	-.023 (.011)*/-*.024*	.006 (.020)/*.006*	-.012 (.041)/-*.012*	-.017 (.014)/-*.017*	-.022 (.030)/-*.021*	-.214 (.406)/-*.073*	-.242 (.283)/ -*.115*
W3 Immig	W2 ID	.001 (.005)/*.001*	-.002 (.004)/-*.002*	.003 (.006)/*.003*	.010 (.011)/*.010*	-.001 (.004)/-*.001*	.005 (.008)/ *.005*	.021 (.268)/ *.198*	-.033 (.036)/ -*.884*
	W2 Immig	.988 (.005)***/ *.992*	.990 (.004)***/ *.992*	.978 (.007)***/ *.984*	.971 (.013)***/ *.979*	.981 (.005)***/ *.985*	.982 (.010)***/ *.984*	-.244 (.530)/-*.950*	.072 (.097)/ *1.129*

trait cov							-.007 (.002)***/-*.200*	-.007 (.002)***/-*.199*
W1 ID-Immig cov	-.007 (.002)***/ -*.181*	-.007 (.002)***/ -*.181*	-.007 (.002)***/ -*.189*	-.009 (.004)*/ -*.192*	-.007 (.002)***/ -*.189*	-.009 (.004)*/ -*.192*	.000 (.000)/ *.135*	.000 (.000)/ *.170*
W2 ID-Immig cov	-.000 (.000)/-*.015*	-.000 (.000)/-*.014*	-.000 (.000)/-*.023*	-.000 (.000)/-*.198*	-.000 (.000)/ -*.024*	-.000 (.000)*/ -*.199*	.000 (.001)/ *.098*	-.000 (.000)/ -*.198*
W3 ID-Immig cov	-.000 (.000)/-*.020*	-.000 (.000)/-*.019*	-.000 (.000)/-*.015*	.000 (.000)/*.027*	-.000 (.000)/ -*.016*	.000 (.000)/ *.027*	-.000 (.000)/-*.393*	-.000 (.000)/ -*.294*
params	17	17	149	149	149	149	20	20
N	630	630	612	124	612	124	630	630
CFI	.825	.825	.850	.850	.850	.850	1.000	1.000
RMSEA	.797	.563	.797	.827	.564	.584	.019	.000
SRMR	.014	.016	.005	.004	.005	.006	.005	.006
Chisq (df)	1603.925 (4)***	1607.563 (8)***	1558.587 (4)***	343.426 (4)***	1563.083 (8)***	346.786 (8)***	1.227 (1)	2.276 (5)
Chisq test		3.638 (4)			4.496 (4)	3.360 (4)	1602.698 (3)***	1.049 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

[a] Starting values from failed CLPM w/ stationarity (a1, b1, a2, & b2, W1-W2 only).
[b] Negative variance (cimmig_w3 var = -.000, SE = .000, n.s.). If fix negative variance to 0, warning that covariance matrix of latent variables is not positive definite. Estimates from model with negative variance (to be comparable to model without stationarity).

Table A18

Study 1 Asian American Identity & Criminal Justice Attitudes (continuous indicators) Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.825 (.023)***/ *.821*	.861 (.015)***/ *.832*	.803 (.024)***/ *.795*	.793 (.053)***/ *.797*	.845 (.015)***/ *.811*	.829 (.034)***/ *.809*	-.043 (.231)/-*.042*	-.003 (.095)/-*.004*
	W1 Crim	.016 (.020)/*.018*	.003 (.013)/ *.003*	-.006 (.025)/-*.006*	-.066 (.052)/-*.082*	.003 (.017)/ *.003*	-.017 (.034)/-*.020*	.095 (.682)/*.046*	-.318 (.200)/-*.188*
W2 Crim	W1 ID	.005 (.010)/*.004*	.009 (.007)/ *.008*	.000 (.011)/*.000*	.006 (.023)/*.005*	.007 (.007)/ *.006*	.005 (.015)/ *.004*	-.111 (.109)/-*.299*	-.065 (.040)/-*.235*
	W1 Crim	.966 (.009)***/ *.972*	.975 (.006)***/ *.973*	.948 (.012)***/ *.954*	.951 (.022)***/ *.956*	.955 (.008)***/ *.957*	.959 (.015)***/ *.960*	-.125 (.333)/-*.170*	-.114 (.218)/-*.178*
W3 ID	W2 ID	.886 (.019)***/ *.876*	.861 (.015)***/ *.875*	.876 (.021)***/ *.867*	.860 (.046)***/ *.837*	.845 (.015)***/ *.864*	.829 (.034)***/ *.832*	.326 (.121)**/ *.307*	-.003 (.095)/-*.002*
	W2 Crim	-.008 (.017)/-*.008*	.003 (.013)/ *.003*	.009 (.022)/*.010*	.025 (.045)/*.030*	.003 (.017)/ *.003*	-.017 (.034)/-*.020*	.197 (.345)/*.067*	-.318 (.200)/-*.111*
W3 Crim	W2 ID	.011 (.010)/*.010*	.009 (.007)/ *.008*	.013 (.010)/*.012*	.005 (.022)/*.004*	.007 (.007)/ *.007*	.005 (.015)/ *.004*	.151 (.168)/*.311*	-.065 (.040)/-*.114*
	W2 Crim	.983 (.009)***/ *.976*	.975 (.006)***/ *.976*	.961 (.011)***/ *.955*	.968 (.021)***/ *.971*	.955 (.008)***/ *.953*	.959 (.015)***/ *.967*	-.029 (.507)/-*.022*	-.114 (.218)/-*.075*

trait cov							.000 (.002)/*.011*	.001 (.001)/ *.025*
W1 ID-Crim cov	-.000 (.002)/-*.005*	-.000 (.002)/-*.005*	.000 (.002)/*.002*	.004 (.004)/*.084*	.000 (.002)/ *.002*	.004 (.004)/ *.084*	-.001 (.000)/-*.245*	-.000 (.000)/-*.045*
W2 ID-Crim cov	.000 (.000)/*.053*	.000 (.000)/ *.053*	.000 (.000)/*.029*	-.000 (.000)/-*.078*	.000 (.000)/ *.031*	-.000 (.000)/-*.075*	.001 (.001)/*.258*	-.001 (.000)/-*.425*
W3 ID-Crim cov	.000 (.000)/*.017*	.000 (.000)/ *.017*	.000 (.000)/*.023*	-.000 (.000)/-*.012*	.000 (.000)/ *.024*	-.000 (.000)/-*.009*	.000 (.000)/*.148*	.000 (.000)/ *.090*
params	17	17	149	149	149	149	20	20
N	628	628	610	125	610	125	628	628
CFI	.969	.968	.976	.975	.976	.976	1.000	.998
RMSEA	.263	.188	.255	.275	.182	.192	.000	.052
SRMR	.021	.026	.008	.007	.010	.011	.003	.026
Chisq (df)	178.205 (4)***	185.011 (8)***	162.157 (4)***	41.825 (4)***	168.900 (8)***	45.026 (8)***	0.204 (1)	13.622 (5)*
Chisq test		6.806 (4)			6.743 (4)	3.201 (4)		13.418 (4)**

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A19

Study 1 Asian American Identity & Criminal Justice Attitudes (categorical indicator) Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM[a]**	**RI-CLPM, stationarity[b]**
W2 ID	W1 ID	.825 (.023)***/ *.821*	.861 (.015)***/ *.832*	.803 (.024)***/ *.795*	.794 (.053)***/ *.797*	.845 (.015)***/ *.811*	.829 (.034)***/ *.809*	.467 (.980)/*.453*	.035 (.100)/ *.046*
	W1 Crim	.018 (.019)/ *.021*	.001 (.012)/ *.001*	-.006 (.025)/-*.008*	-.066 (.051)/-*.085*	-.002 (.016)/-*.003*	-.016 (.034)/-*.020*	5.415 (8.086)/ *1.064*	-.719 (.390)$^{+}$/-*.227*
W2 Crim	W1 ID	.001 (.006)/ *.001*	.004 (.004)/ *.003*	-.001 (.006)/-*.001*	.002 (.013)/*.001*	.002 (.004)/ *.002*	.000 (.009)/ *.000*	-.182 (.243)/-*.891*	-.047 (.024)$^{+}$/-.596
	W1 Crim	.995 (.005)***/ *.992*	.999 (.003)***/ *.992*	.990 (.006)***/ *.987*	.993 (.012)***/ *.986*	.991 (.004)***/ *.987*	.993 (.009)***/ *.986*	-1.036 (1.172)/-*1.027*	-.271 (.038)***/-.833
W3 ID	W2 ID	.887 (.019)***/ *.876*	.861 (.015)***/ *.875*	.876 (.021)***/ *.867*	.859 (.046)***/ *.836*	.845 (.015)***/ *.864*	.829 (.034)***/ *.832*	.267 (.187)/*.255*	.035 (.100)/ *.034*
	W2 Crim	-.013 (.016)/-*.015*	.001 (.012)/ *.001*	.001 (.021)/*.001*	.023 (.044)/*.029*	-.002 (.016)/-*.003*	-.016 (.034)/-*.020*	.334 (.541)/*.063*	-.719 (.390)$^{+}$/-.071
W3 Crim	W2 ID	.005 (.006)/ *.004*	.004 (.004)/ *.003*	.006 (.006)/*.005*	-.001 (.013)/-*.001*	.002 (.004)/ *.002*	.000 (.009)/ *.000*	.163 (.108)/*.389*	-.047 (.024)$^{+}$/-*.123*
	W2 Crim	1.002 (.005)***/ *.993*	.999 (.003)***/ *.993*	.992 (.006)***/ *.982*	.993 (.012)***/ *.989*	.991 (.004)***/ *.982*	.993 (.009)***/ *.989*	.332 (.426)/*.158*	-.271 (.038)***/-.073

trait cov							.000 (.002)/*.009*	.001 (.002)/ *.024*
W1 ID-Crim cov	.000 (.002)/ *.007*	.000 (.002)/ *.007*	.001 (.002)/*.013*	.004 (.004)/*.093*	.001 (.002)/ *.013*	.004 (.004)/ *.093*	-.001 (.000)/-*.464*	-.000 (.000)/ -*.050*
W2 ID-Crim cov	.000 (.000)+/*.070*	.000 (.000)+/*.070*	.000 (.000)/*.049*	-.000 (.000)/-*.017*	.000 (.000)/ *.051*	-.000 (.000)/-*.017*	.002 (.002)	-.000 (.000)+
W3 ID-Crim cov	.000 (.000)/ *.029*	.000 (.000)/ *.028*	.000 (.000)/*.034*	.000 (.000)/*.027*	.000 (.000)/ *.035*	.000 (.000)/ *.027*	.000 (.000)/*.065*	.000 (.000)/ *.148*
params	17	17	149	149	149	149	19	20
N	628	628	610	125	610	125	628	628
CFI	.981	.980	.985	.986	.985	.987	1.000	.999
RMSEA	.231	.165	.225	.224	.160	.154	.000	.052
SRMR	.021	.026	.008	.007	.009	.011	.006	.026
Chisq (df)	138.253 (4)***	145.220 (8)***	127.337 (4)***	28.987 (4)***	133.234 (8)***	31.812 (8)***	1.328 (2)	16.088 (6)*
Chisq test		6.967 (4)			5.897 (4)	2.825 (4)		14.760 (4)**

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

[a] Did not converge initially. Converges if set ccrim2_w2 var = 0, but warning: covariance matrix of latent variables is not positive definite. Estimates from model fixing negative variance to 0.
[b] Negative variance (ccrim2_w2 var = -.000, SE = .000, n.s.). If fix negative variance to 0, warning that covariance matrix of latent variables is not positive definite. Estimates from model fixing negative variance to 0.

Table A20

Study 1 POC Identity & Criminal Justice Attitudes (continuous indicators) Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.889 (.018)***/ *.891*	.907 (.013)***/ *.896*	.877 (.020)***/ *.876*	.891 (.049)***/ *.870*	.892 (.014)***/ *.881*	.858 (.033)***/ *.857*	-.017 (.271)/-*.017*	.108 (.145)/ *.123*
	W1 Crim	.022 (.021)/*.019*	.011 (.015)/ *.009*	.010 (.026)/*.008*	-.027 (.055)/-*.028*	-.010 (.019)/-*.009*	-.023 (.037)/-*.024*	-.104 (.649)/-*.052*	-.394 (.274)/-*.199*
W2 Crim	W1 ID	.006 (.008)/*.007*	.008 (.006)/ *.010*	.001 (.009)/*.002*	.013 (.020)/*.012*	.002 (.006)/ *.003*	.008 (.013)/ *.007*	-.072 (.080)/-*.201*	-.071 (.053)/-*.212*
	W1 Crim	.965 (.009)***/ *.971*	.973 (.006)***/ *.971*	.948 (.012)***/ *.954*	.951 (.022)***/ *.956*	.955 (.008)***/ *.957*	.960 (.015)***/ *.960*	-.053 (.257)/-*.073*	.000 (.233)/ *.000*
W3 ID	W2 ID	.925 (.019)***/ *.893*	.907 (.013)***/ *.890*	.907 (.021)***/ *.875*	.829 (.044)***/ *.840*	.892 (.014)***/ *.871*	.858 (.033)***/ *.846*	.294 (.149)*/*.221*	.108 (.145)/ *.089*
	W2 Crim	-.001 (.022)/-*.001*	.011 (.015)/ *.009*	-.033 (.028)/-*.028*	-.016 (.052)/-*.016*	-.010 (.019)/-*.009*	-.023 (.037)/-*.024*	-.305 (.474)/-*.082*	-.394 (.274)/-*.122*
W3 Crim	W2 ID	.011 (.008)/*.012*	.008 (.006)/ *.010*	.003 (.008)/*.004*	.001 (.018)/*.001*	.002 (.006)/ *.003*	.008 (.013)/ *.007*	.009 (.143)/ *.019*	-.071 (.053)/-*.154*
	W2 Crim	.980 (.009)***/ *.974*	.973 (.006)***/ *.974*	.961 (.011)***/ *.955*	.968 (.021)***/ *.971*	.955 (.008)***/ *.953*	.960 (.015)***/ *.967*	-.003 (.481)/-*.002*	.000 (.233)/ *.000*

trait cov							.010 (.002)***/ *.212*	.010 (.002)***/ *.216*
W1 ID-Crim cov	.010 (.002)***/ *.196*	.010 (.002)***/ *.196*	.010 (.002)***/ *.192*	.013 (.005)**/ *.241*	.010 (.002)***/ *.192*	.013 (.005)**/ *.241*	-.000 (.001)/-*.102*	-.000 (.000)/-*.103*
W2 ID-Crim cov	.000 (.000)/*.002*	.000 (.000)/ *.002*	.000 (.000)/*.013*	-.001 (.000)*/-*.185*	.000 (.000)/ *.013*	-.001 (.000)*/-*.183*	-.000 (.001)/-*.139*	-.001 (.001)/-*.354*
W3 ID-Crim cov	-.000 (.000)/-*.005*	-.000 (.000)/-*.006*	-.000 (.000)/-*.001*	.000 (.000)/*.038*	-.000 (.000)/-*.002*	.000 (.000)/ *.040*	-.000 (.000)/-*.017*	-.000 (.000)/-*.010*
params	17	17	149	149	149	149	20	20
N	628	628	610	125	610	125	628	628
CFI	.973	.973	.979	.980	.980	.982	1.000	1.000
RMSEA	.253	.179	.245	.248	.173	.168	.021	.000
SRMR	.015	.017	.005	.005	.006	.007	.006	.011
Chisq (df)	165.301 (4)***	169.382 (8)***	150.895 (4)***	34.797 (4)***	153.835 (8)***	36.298 (8)***	1.265 (1)	4.548 (5)
Chisq test		4.081 (4)			2.940 (4)	1.501 (4)		3.283 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A21

Study 1 POC Identity & Criminal Justice Attitudes (categorical indicator) Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2[a]**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM[b]**	**RI-CLPM, stationarity[c]**
W2 ID	W1 ID	.889 (.018)***/ *.890*	.906 (.013)***/ *.895*	.877 (.020)***/ *.876*	.892 (.049)***/ *.872*	.892 (.014)***/ *.881*	.858 (.033)***/ *.858*	-.230 (.925)/-*.233*	.229 (.128)$^{+}$/ *.226*
	W1 Crim	.022 (.020)/*.020*	.015 (.014)/ *.014*	.010 (.025)/ *.009*	-.041 (.054)/-*.044*	-.006 (.018)/-*.005*	-.016 (.037)/-*.018*	-4.743 (14.153)/-*.638*	-1.166 (.529)*/-*.277*
W2 Crim	W1 ID	-.001 (.005)/-*.001*	.002 (.003)/ *.002*	-.001 (.005)/-*.001*	.007 (.011)/ *.006*	-.000 (.004)/-*.000*	.004 (.008)/ *.003*	-.134 (.301)/-*.562*	-.068 (.032)*/-*.761*
	W1 Crim	.995 (.005)***/ *.992*	.998 (.004)***/ *.992*	.990 (.006)***/ *.987*	.993 (.012)***/ *.986*	.991 (.004)***/ *.987*	.993 (.009)***/ *.986*	-1.816 (2.533)/-*1.017*	-.278 (.039)***/-*.756*
W3 ID	W2 ID	.924 (.019)***/ *.892*	.906 (.013)***/ *.889*	.907 (.021)***/ *.875*	.829 (.044)***/ *.840*	.892 (.014)***/ *.871*	.858 (.033)***/ *.846*	.274 (.154)$^{+}$/*.203*	.229 (.128)$^{+}$/ *.204*
	W2 Crim	.007 (.021) *.006*	.015 (.014)/ *.013*	-.023 (.027)/-*.020*	.004 (.050)/ *.004*	-.006 (.018)/-*.005*	-.016 (.037)/-*.018*	-.287 (.481)/-*.051*	-1.166 (.529)*/-*.091*
W3 Crim	W2 ID	.004 (.005)/*.004*	.002 (.003)/ *.002*	.000 (.005)/ *.000*	-.000 (.011)/-*.000*	-.000 (.004)/-*.000*	.004 (.008)/ *.003*	-.022 (.067)/-*.059*	-.068 (.032)*/-*.227*

W2 Crim	1.002 (.005)***/ *.992*	.998 (.004)***/ *.992*	.992 (.006)***/ *.982*	.993 (.012)***/ *.989*	.991 (.004)***/ *.982*	.993 (.009)***/ *.989*	.568 (.222)*/ *.370*	-.278 (.039)***/- *.082*
trait cov							.012 (.002)***/ *.243*	.012 (.002)***/ *.245*
W1 ID-Crim cov	.012 (.002)***/ *.229*	.012 (.002)***/ *.229*	.012 (.002)***/ *.225*	.015 (.005)**/ *.269*	.012 (.002)***/ *.225*	.015 (.005)**/ *.269*	-.000 (.001)/-*.306*	-.000 (.000)/ -*.131*
W2 ID-Crim cov	.000 (.000)/*.019*	.000 (.000)/ *.020*	.000 (.000)/ *.031*	-.000 (.000)/-*.133*	.000 (.000)/ *.031*	-.000 (.000)/-*.131*	-.001 (.003)	-.001 (.000)
W3 ID-Crim cov	-.000 (.000)/-*.022*	-.000 (.000)/ -*.022*	-.000 (.000)/-*.013*	.000 (.000)/ *.043*	-.000 (.000)/ -*.013*	.000 (.000)/ *.045*	-.000 (.000)/-*.023*	.000 (.000)/ *.058*
params	17	17	149	149	149	149	19	20
N	628	628	610	125	610	125	628	628
CFI	.984	.984	.987	.991	.987	.992	1.000	1.000
RMSEA	.220	.155	.214	.182	.150	.118	.012	.013
SRMR	.014	.016	.005	.005	.006	.007	.006	.009
Chisq (df)	125.364 (4)***	128.816 (8)***	115.953 (4)***	20.473 (4)***	117.841 (8)***	21.981 (8)**	2.196 (2)	6.615 (6)
Chisq test		3.452 (4)			1.888 (4)	1.508 (4)		4.419 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.
Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

[a] Starting values from OLS (lagged & cross-lagged coefficients, both lags).

[b] Did not converge initially. Converges if set ccrim2_w2 var = 0, but warning: covariance matrix of latent variables is not positive definite. Estimates from model fixing negative variance to 0.

[c] Negative variance (ccrim2_w2 var = -.000, SE = .000, n.s.). If fix negative variance to 0, warning that covariance matrix of latent variables is not positive definite. Estimates from model fixing negative variance to 0.

Table A22

Study 1 American Identity & Criminal Justice Attitudes (continuous indicators) Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.909 (.016)***/ *.919*	.926 (.011)***/ *.921*	.909 (.017)***/ *.918*	.907 (.033)***/ *.922*	.916 (.012)***/ *.920*	.924 (.023)***/ *.926*	-.166 (.214)/-*.196*	-.105 (.144)/-*.140*
	W1 Crim	.002 (.015)/ *.002*	-.006 (.010)/-*.006*	-.004 (.018)/-*.004*	-.018 (.037)/-*.020*	-.003 (.013)/-*.003*	-.000 (.026)/-*.000*	.430 (.383)/ *.352*	.094 (.198)/ *.083*
W2 Crim	W1 ID	-.011 (.010)/-*.010*	-.003 (.007)/-*.002*	-.006 (.011)/-*.005*	-.005 (.020)/-*.004*	.004 (.007)/ *.004*	.012 (.014)/ *.011*	-.042 (.141)/-*.077*	.022 (.078)/ *.050*
	W1 Crim	.965 (.009)***/ *.972*	.975 (.006)***/ *.973*	.948 (.012)***/ *.954*	.952 (.022)***/ *.957*	.955 (.008)***/ *.957*	.960 (.015)***/ *.960*	-.008 (.317)/-*.010*	-.076 (.226)/-*.114*
W3 ID	W2 ID	.943 (.015)***/ *.927*	.926 (.011)***/ *.927*	.922 (.016)***/ *.909*	.940 (.032)***/ *.913*	.916 (.012)***/ *.908*	.924 (.023)***/ *.910*	.051 (.221)/ *.041*	-.105 (.144)/-*.083*
	W2 Crim	-.013 (.014)/-*.014*	-.006 (.010)/-*.007*	-.002 (.018)/-*.002*	.017 (.036)/ *.017*	-.003 (.013)/-*.003*	-.000 (.026)/-*.000*	-.260 (.387)/-*.132*	.094 (.198)/ *.044*
W3 Crim	W2 ID	.005 (.009)/ *.005*	-.003 (.007)/-*.002*	.013 (.010)/ *.012*	.027 (.019)/ *.025*	.004 (.007)/ *.004*	.012 (.014)/ *.011*	.133 (.198)/ *.162*	.022 (.078)/ *.027*
	W2 Crim	.983 (.009)***/ *.977*	.975 (.006)***/ *.976*	.961 (.011)***/ *.955*	.967 (.021)***/ *.970*	.955 (.008)***/ *.953*	.960 (.015)***/ *.967*	.157 (.374)/ *.122*	-.076 (.226)/-*.054*

trait cov							-.003 (.002)*/-*.088*	-.003 (.002)*/-*.087*
W1 ID-Crim cov	-.003 (.002)$^+$/ -*.078*	-.003 (.002)$^+$/ -*.078*	-.003 (.002)$^+$/ -*.077*	-.000 (.005)/-*.005*	-.003 (.002)$^+$/ -*.077*	-.000 (.005)/-*.005*	.000 (.000)/ *.094*	.000 (.000)/ *.026*
W2 ID-Crim cov	-.000 (.000)/-*.058*	-.000 (.000)/-*.057*	-.000 (.000)/-*.050*	-.000 (.000)/-*.129*	-.000 (.000)/-*.049*	-.000 (.000)/-*.123*	.000 (.001)/ *.054*	-.000 (.000)/-*.014*
W3 ID-Crim cov	-.000 (.000)/-*.043*	-.000 (.000)/-*.042*	-.000 (.000)/-*.040*	-.000 (.000)$^+$/ -*.160*	-.000 (.000)/-*.039*	-.000 (.000)$^+$/ -*.155*	-.000 (.000)/-*.060*	.000 (.000)/ *.002*
params	17	17	149	149	149	149	20	20
N	628	628	610	125	610	125	628	628
CFI	.966	.966	.975	.973	.975	.974	1.000	1.000
RMSEA	.293	.208	.278	.307	.196	.215	.000	.000
SRMR	.014	.018	.005	.004	.005	.006	.001	.005
Chisq (df)	219.779 (4)***	226.135 (8)***	192.818 (4)***	51.214 (4)***	195.345 (8)***	54.333 (8)***	0.037 (1)	1.980 (5)
Chisq test		6.356 (4)			2.527 (4)	3.119 (4)		1.943 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A23

Study 1 American Identity & Criminal Justice Attitudes (categorical indicator) Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3[a]**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM[b]**	**RI-CLPM, stationarity[c]**
W2 ID	W1 ID	.909 (.016)***/ *.919*	.926 (.011)***/ *.920*	.908 (.017)***/ *.917*	.907 (.033)***/ *.922*	.916 (.012)***/ *.920*	.926 (.023)***/ *.927*	-23.747/-*28.840*	-.099 (.145)/ -*.130*
	W1 Crim	-.004 (.014)/-*.004*	-.011 (.010)/-*.012*	-.013 (.018)/-*.015*	-.026 (.037)/-*.029*	-.011 (.012)/-*.012*	-.005 (.025)/-*.006*	400.903/ *31.198*	.224 (.386)/ *.109*
W2 Crim	W1 ID	-.005 (.006)/-*.004*	-.002 (.004)/-*.001*	-.004 (.006)/-*.003*	.002 (.011)/ *.001*	.002 (.004)/ *.002*	.010 (.008)/ *.009*	9.001/ *40.360*	.026 (.048)/ *.243*
	W1 Crim	.995 (.005)***/ *.992*	.999 (.003)***/ *.992*	.990 (.006)***/ *.987*	.993 (.012)***/ *.987*	.991 (.004)***/ *.987*	.994 (.009)***/ *.987*	-152.66/-*43.864*	-.281 (.037)***/-*.985*
W3 ID	W2 ID	.942 (.015)***/ *.926*	.926 (.011)***/ *.927*	.922 (.016)***/ *.909*	.940 (.032)***/ *.913*	.916 (.012)***/ *.908*	.926 (.023)***/ *.911*	.044/ *.034*	-.099 (.145)/ -*.079*
	W2 Crim	-.018 (.013)/-*.020*	-.011 (.010)/-*.012*	-.009 (.017)/-*.011*	.014 (.035)/ *.015*	-.011 (.012)/-*.012*	-.005 (.025)/-*.006*	-.170/-*.036*	.224 (.386)/ *.025*
W3 Crim	W2 ID	.002 (.006)/ *.001*	-.002 (.004)/-*.001*	.007 (.006)/ *.006*	.016 (.011)/ *.015*	.002 (.004)/ *.002*	.010 (.008)/ *.009*	.127/ *.193*	.026 (.048)/ *.044*
	W2 Crim	1.003 (.005)***/ *.993*	.999 (.003)***/ *.993*	.992 (.006)***/ *.983*	.993 (.012)***/ *.989*	.991 (.004)***/ *.982*	.994 (.009)***/ *.989*	.576/ *.237*	-.281 (.037)***/-*.067*

trait cov							-.005/-*.126*	-.005 (.002)**/-*.120*
W1 ID-Crim cov	-.005 (.002)**/ -*.112*	-.005 (.002)**/ -*.112*	-.005 (.002)**/ -*.115*	-.003 (.005)/-*.049*	-.005 (.002)**/ -*.115*	-.003 (.005)/-*.049*	.000/ *.919*	.000 (.000)/ *.063*
W2 ID-Crim cov	-.000 (.000)/-*.026*	-.000 (.000)/-*.026*	-.000 (.000)/-*.018*	-.000 (.000)/-*.010*	-.000 (.000)/-*.017*	-.000 (.000)/-*.006*	.121/ *1.010*	.000 (.000)
W3 ID-Crim cov	-.000 (.000)/-*.059*	-.000 (.000)/-*.059*	-.000 (.000)/-*.055*	-.000 (.000)*/-*.222*	-.000 (.000)/-*.054*	-.000 (.000)*/-*.219*	-.000/-*.067*	-.000 (.000)/ -*.082*
params	17	17	149	149	149	149	20	20
N	628	628	610	125	610	125	628	628
CFI	.978	.978	.983	.983	.983	.984		1.000
RMSEA	.264	.187	.250	.260	.176	.179		.000
SRMR	.014	.017	.005	.004	.005	.005		.006
Chisq (df)	179.084 (4)***	184.074 (8)***	157.105 (4)***	37.830 (4)***	159.020 (8)***	40.092 (8)***		5.043 (6)
Chisq test		4.990 (4)			1.915 (4)	2.262 (4)		

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.
Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

[a] Starting values from OLS (lagged & cross-lagged coefficients, both lags).
[b] Did not converge initially. Constraining ccrim2_w2 var = 0 converged with a different negative residual variance. Estimates are from original model.
[c] Negative variance (ccrim2_w2 var = -.000, SE = .000, n.s.). If fix negative variance to 0, warning that covariance matrix of latent variables is not positive definite. Estimates from model fixing negative variance to 0.

Table A24

Study 1 Asian American Identity & Affirmative Action Attitudes Panel Model Results

		CLPM Model 1	CLPM Model 1, stationarity	CLPM Model 2	CLPM Model 3	CLPM Model 2, stationarity	CLPM Model 3, stationarity	RI-CLPM	RI-CLPM, stationarity
W2 ID	W1 ID	.822 (.023)***/ *.819*	.858 (.015)***/ *.830*	.801 (.024)***/ *.795*	.785 (.053)***/ *.788*	.842 (.015)***/ *.809*	.828 (.034)***/ *.807*	-.055 (.192)/-*.054*	-.010 (.092)/-*.014*
	W1 Aff	.024 (.015)/ *.036*	.018 (.010)+/*.026*	.017 (.018)/ *.025*	-.007 (.039)/-*.011*	.026 (.011)*/*.038*	.024 (.026)/ *.036*	.016 (.092)/ *.026*	-.003 (.042)/-*.006*
W2 Aff	W1 ID	.043 (.036)/ *.029*	.042 (.024)+/*.027*	.056 (.038)/ *.037*	.134 (.089)/ *.090*	.035 (.024)/ *.023*	.058 (.058)/ *.038*	.036 (.228)/ *.023*	.074 (.109)/ *.061*
	W1 Aff	.786 (.024)***/ *.795*	.818 (.016)***/ *.806*	.729 (.028)***/ *.738*	.600 (.066)***/ *.625*	.758 (.018)***/ *.756*	.643 (.044)***/ *.656*	-.091 (.135)/-*.097*	-.068 (.090)/-*.085*
W3 ID	W2 ID	.885 (.020)***/ *.874*	.858 (.015)***/ *.872*	.873 (.021)***/ *.864*	.856 (.046)***/ *.833*	.842 (.015)***/ *.861*	.828 (.034)***/ *.831*	.342 (.097)***/ *.317*	-.010 (.092)/-*.009*
	W2 Aff	.012 (.013)/ *.017*	.018 (.010)+/*.027*	.031 (.015)*/*.045*	.045 (.035)/ *.065*	.026 (.011)*/*.038*	.024 (.026)/ *.036*	.043 (.062)/ *.060*	-.003 (.042)/-*.004*
W3 Aff	W2 ID	.037 (.032)/ *.025*	.042 (.024)+/*.029*	.017 (.033)/ *.011*	-.010 (.079)/-*.007*	.035 (.024)/ *.024*	.058 (.058)/ *.043*	.291 (.173)+/*.189*	.074 (.109)/ *.044*
	W2 Aff	.845 (.022)***/ *.842*	.818 (.016)***/ *.840*	.781 (.024)***/ *.777*	.684 (.061)***/ *.723*	.758 (.018)***/ *.768*	.643 (.044)***/ *.699*	.105 (.121)/ *.103*	-.068 (.090)/-*.067*

trait cov							.005 (.002)*/*.116*	.006 (.002)**/ *.132*
W1 ID-Aff cov	.004 (.002)*/*.085*	.004 (.002)*/*.085*	.004 (.002)*/*.086*	-.002 (.005)/-*.040*	.004 (.002)*/*.086*	-.002 (.005)/-*.040*	-.001 (.001)/-*.060*	.001 (.001)/ *.044*
W2 ID-Aff cov	.001 (.001)/ *.035*	.001 (.001)/ *.034*	.000 (.001)/ *.029*	.001 (.002)/ *.041*	.000 (.001)/ *.029*	.001 (.002)/ *.039*	.001 (.002)/ *.140*	-.000 (.001)/-*.001*
W3 ID-Aff cov	-.000 (.001)/-*.012*	-.000 (.001)/-*.013*	-.000 (.001)/-*.007*	.000 (.001)/ *.011*	-.000 (.001)/-*.007*	.000 (.001)/ *.010*	.001 (.001)/ *.064*	.000 (.001)/ *.006*
params	17	17	149	149	149	149	20	20
N	632	632	614	126	614	126	632	632
CFI	.936	.934	.960	.959	.959	.959	1.000	.997
RMSEA	.289	.206	.270	.273	.193	.194	.000	.054
SRMR	.037	.041	.012	.014	.014	.017	.005	.031
Chisq (df)	214.542 (4)***	222.405 (8)***	183.477 (4)***	41.597 (4)***	191.728 (8)***	45.918 (8)***	0.766 (1)	14.321 (5)*
Chisq test		7.863 (4)$^{+}$			8.251 (4)$^{+}$	4.321 (4)		13.555 (4)**

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A25

Study 1 POC Identity & Affirmative Action Attitudes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.866 (.019)***/ *.866*	.889 (.014)***/ *.880*	.861 (.020)***/ *.859*	.875 (.051)***/ *.853*	.882 (.015)***/ *.873*	.851 (.034)***/ *.847*	.040 (.216)/ *.040*	.139 (.125)/ *.152*
	W1 Aff	.062 (.017)***/ *.071*	.039 (.012)**/ *.044*	.065 (.019)***/ *.076*	.034 (.043)/ *.044*	.032 (.013)*/*.037*	.013 (.030)/ *.017*	.114 (.099)/ *.171*	.107 (.049)*/*.169*
W2 Aff	W1 ID	.114 (.029)***/ *.100*	.073 (.020)***/ *.062*	.085 (.031)**/ *.074*	.140 (.082)$^{+}$/*.111*	.049 (.021)*/*.042*	.078 (.053)/ *.061*	.258 (.238)/ *.183*	.364 (.116)**/ *.280*
	W1 Aff	.750 (.025)***/ *.759*	.795 (.017)***/ *.786*	.714 (.029)***/ *.722*	.558 (.069)***/ *.581*	.748 (.019)***/ *.747*	.623 (.046)***/ *.636*	-.138 (.132)/-*.145*	-.036 (.088)/-*.041*
W3 ID	W2 ID	.919 (.020)***/ *.888*	.889 (.014)***/ *.873*	.908 (.022)***/ *.877*	.830 (.046)***/ *.841*	.882 (.015)***/ *.861*	.851 (.034)***/ *.841*	.286 (.144)*/*.229*	.139 (.107)/ *.127*
	W2 Aff	.010 (.018)/ *.011*	.039 (.012)**/ *.044*	-.008 (.020)/-*.009*	-.003 (.042)/-*.003*	.032 (.013)*/*.036*	.013 (.030)/ *.017*	-.016 (.089)/-*.018*	.107 (.049)*/*.127*
W3 Aff	W2 ID	.036 (.027)/ *.031*	.073 (.020)***/ *.064*	.018 (.028)/ *.016*	.029 (.069)/ *.025*	.049 (.021)*/*.043*	.078 (.053)/ *.067*	.198 (.174)/ *.131*	.364 (.116)**/ *.256*

W2 Aff	.835 (.024)***/*.831*	.795 (.017)***/*.815*	.777 (.025)***/*.773*	.675 (.064)***/*.714*	.748 (.019)***/*.758*	.623 (.046)***/*.678*	.105 (.117)/*.099*	-.036 (.088)/-*.036*
trait cov							.025 (.003)***/*.442*	.025 (.003)***/*.431*
W1 ID-Aff cov	.026 (.003)***/*.391*	.026 (.003)***/*.391*	.026 (.003)***/*.384*	.027 (.006)***/*.418*	.026 (.003)***/*.384*	.027 (.006)***/*.418*	.001 (.001)/*.088*	.001 (.001)/*.048*
W2 ID-Aff cov	.002 (.001)**/*.104*	.002 (.001)*/*.099*	.002 (.001)*/*.096*	.002 (.002)/*.125*	.002 (.001)*/*.091*	.002 (.002)/*.123*	.003 (.002)⁺/*.382*	.005 (.001)**/*.522*
W3 ID-Aff cov	.001 (.001)*/*.080*	.001 (.001)⁺/*.074*	.001 (.001)/*.066*	.004 (.001)*/*.227*	.001 (.001)/*.061*	.004 (.001)*/*.226*	.000 (.001)/*.009*	.000 (.001)/*.032*
params	17	17	149	149	149	149	20	20
N	632	632	614	126	614	126	632	632
CFI	.949	.946	.966	.967	.964	.968	.999	.999
RMSEA	.277	.201	.261	.253	.189	.177	.055	.028
SRMR	.033	.037	.011	.014	.012	.016	.010	.016
Chisq (df)	198.373 (4)***	212.368 (8)***	170.880 (4)***	36.218 (4)***	184.177 (8)***	39.517 (8)***	2.916 (1)⁺	7.470 (5)
Chisq test		13.995 (4)**			13.297 (4)**	3.299 (4)		4.554 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A26

Study 1 American Identity & Affirmative Action Attitudes Panel Model Results

		CLPM Model 1	**CLPM Model 1, stationarity**	**CLPM Model 2**	**CLPM Model 3**	**CLPM Model 2, stationarity**	**CLPM Model 3, stationarity**	**RI-CLPM**	**RI-CLPM, stationarity**
W2 ID	W1 ID	.909 (.016)***/ *.920*	.925 (.011)***/ *.920*	.908 (.017)***/ *.918*	.902 (.034)***/ *.918*	.915 (.012)***/ *.919*	.920 (.023)***/ *.922*	-.062 (.169)/-*.075*	.071 (.146)/ *.076*
	W1 Aff	.008 (.011)/*.011*	-.008 (.007)/-*.012*	.009 (.013)/*.013*	.010 (.029)/*.014*	-.004 (.009)/-*.006*	-.005 (.020)/-*.007*	.062 (.054)/ *.161*	.070 (.036)$^+$/*.166*
W2 Aff	W1 ID	-.022 (.034)/-*.015*	-.001 (.023)/-*.000*	-.024 (.037)/-*.017*	.037 (.079)/*.029*	-.006 (.024)/-*.004*	.011 (.052)/ *.008*	-.170 (.369)/-*.084*	.439 (.177)*/ *.224*
	W1 Aff	.787 (.024)***/ *.796*	.821 (.016)***/ *.809*	.730 (.028)***/ *.739*	.596 (.067)***/ *.620*	.760 (.018)***/ *.757*	.639 (.044)***/ *.652*	-.071 (.134)/-*.076*	-.006 (.096)/-*.007*
W3 ID	W2 ID	.941 (.015)***/ *.925*	.925 (.011)***/ *.926*	.921 (.016)***/ *.908*	.942 (.032)***/ *.915*	.915 (.012)***/ *.908*	.920 (.023)***/ *.909*	.028 (.240)/*.023*	.071 (.146)/ *.068*
	W2 Aff	-.024 (.011)*/-*.034*	-.008 (.007)/-*.012*	-.016 (.012)/-*.023*	-.026 (.028)*/-*.033*	-.004 (.009)/-*.006*	-.005 (.020)/-*.006*	-.021 (.084)/-*.044*	.070 (.036)$^+$/ *.141*
W3 Aff	W2 ID	.015 (.031)/*.010*	-.001 (.023)/-*.000*	.007 (.033)/*.005*	-.024 (.070)/-*.020*	-.006 (.024)/-*.004*	.011 (.052)/ *.009*	.614 (.350)$^+$/*.244*	.439 (.177)*/ *.244*
	W2 Aff	.849 (.021)***/ *.845*	.821 (.016)***/ *.843*	.782 (.024)***/ *.778*	.685 (.061)***/ *.724*	.760 (.018)***/ *.771*	.639 (.044)***/ *.697*	.117 (.135)/ *.113*	-.006 (.096)/-*.006*

trait cov							-.005 (.002)**/-*.112*	-.006 (.002)**/-*.123*
W1 ID-Aff cov	-.006 (.002)**/ -*.110*	-.006 (.002)**/ -*.110*	-.006 (.002)**/ -*.111*	-.005 (.006)/-*.072*	-.006 (.002)**/ -*.111*	-.005 (.006)/-*.072*	-.000 (.001)/-*.057*	.000 (.001)/ *.022*
W2 ID-Aff cov	.000 (.001)/*.029*	.000 (.001)/ *.026*	.000 (.000)/*.023*	.003 (.001)**/ *.248*	.000 (.000)/ *.022*	.003 (.001)**/ *.242*	.001 (.001)/ *.196*	.002 (.001)*/ *.409*
W3 ID-Aff cov	.000 (.000)/*.010*	.000 (.000)/ *.008*	.000 (.000)/*.013*	.001 (.001)/*.079*	.000 (.000)/ *.012*	.001 (.001)/ *.071*	.001 (.001)/ *.083*	.000 (.001)/ *.020*
params	17	17	149	149	149	149	20	20
N	632	632	614	126	614	126	632	632
CFI	.940	.939	.962	.965	.962	.965	1.000	.999
RMSEA	.311	.223	.287	.284	.203	.200	.033	.026
SRMR	.033	.037	.011	.012	.011	.014	.008	.016
Chisq (df)	248.532 (4)***	259.858 (8)***	205.785 (4)***	44.688 (4)***	210.575 (8)***	48.148 (8)***	1.700 (1)	7.171 (5)
Chisq test		11.326 (4)*			4.790 (4)	3.460 (4)		5.471 (4)

Note: Coefficients are reported as follows: unstandardized coefficient (SE)/*standardized coefficient*.

Note: $\Delta\chi^2$ for RI-CLPM without stationarity is vs. CLPM Model 1 without stationarity. Otherwise, $\Delta\chi^2$ is for stationarity vs. no stationarity.

Table A27

Study 2 Racial Identity & Nonwhite FT Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
racial	ID	.763	.785	.741	.764	-.075	-.103
ID	w1	(.028)***	(.021)***	(.029)***	(.022)***	(.170)	(.126)
w2	FT	.048	.035	.049	.037	-.077	-.160
	w1	(.029)$^{+}$	(.022)	(.030)$^{+}$	(.022)$^{+}$	(.145)	(.102)
FT	ID	.028	.051	.033	.056	-.222	-.102
w2	w1	(.025)	(.019)**	(.026)	(.020)**	(.128)$^{+}$	(.087)
	FT	.763	.791	.760	.787	-.077	-.006
	w1	(.026)***	(.020)***	(.027)***	(.020)***	(.143)	(.127)
racial	ID	.813	.785	.794	.764	.040	-.103
ID	w2	(.031)***	(.021)***	(.032)***	(.022)***	(.146)	(.126)
w3	FT	.023	.035	.023	.037	-.266	-.160
	w2	(.032)	(.022)	(.033)	(.022)$^{+}$	(.182)	(.102)
FT	ID	.085	.051	.089	.056	.030	-.102
w3	w2	(.029)**	(.019)**	(.031)**	(.020)**	(.130)	(.087)
	FT	.831	.791	.823	.787	.013	-.006
	w2	(.031)***	(.020)***	(.031)***	(.020)***	(.174)	(.127)
ID-FT trait						.012	.012
covariance						(.003)***	(.003)***
W1 ID-FT		.010	.010	.010	.010	-.002	-.002
covariance		(.003)***	(.003)***	(.003)***	(.003)***	(.002)	(.001)
W2 ID-FT		-.001	-.001	-.001	-.000	-.003	-.003
covariance		(.001)	(.001)	(.001)	(.001)	(.002)	(.002)
W3 ID-FT		.001	.001	.001	.001	.000	.000
covariance		(.001)	(.001)	(.001)	(.001)	(.002)	(.001)
CFI		.930	.928	.943	.942	1.000	1.000
RMSEA		.231	.165	.227	.162	.030	.000
SRMR		.040	.047	.020	.023	.010	.015
Chisq (df)		144.394 (4)***	151.719 (8)***	140.085 (4)***	146.547 (8)***	1.576 (1)	4.234 (5)
Chisq test			7.325 (4)		6.462 (4)		2.658 (4)

Note: N = 658 for all models.

Table A28

Study 2 Racial Identity & Nonwhite FT Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
racial ID w2	ID w1	.799 (.046)***	.835 (.036)***	.792 (.047)***	.831 (.037)***	.021 (.351)	.027 (.331)
	FT w1	.036 (.053)	.046 (.041)	-.006 (.057)	.019 (.045)	-.195 (.507)	.136 (.253)
FT w2	ID w1	.047 (.052)	.016 (.036)	.056 (.053)	.025 (.036)	.067 (.331)	.217 (.361)
	FT w1	.749 (.060)***	.802 (.041)***	.711 (.064)***	.777 (.044)***	-.776 (.690)	.066 (.694)
racial ID w3	ID w2	.885 (.056)***	.835 (.036)***	.889 (.057)***	.831 (.037)***	.248 (.324)	.027 (.331)
	FT w2	.059 (.063)	.046 (.041)	.061 (.069)	.019 (.045)	-.064 (.210)	.136 (.253)
FT w3	ID w2	-.008 (.049)	.016 (.036)	.003 (.049)	.025 (.036)	-.109 (.286)	.217 (.361)
	FT w2	.847 (.055)***	.802 (.041)***	.834 (.059)***	.777 (.044)***	.138 (.185)	.066 (.694)
ID-FT trait covariance						.016 (.005)**	.014 (.005)**
W1 ID-FT covariance		.015 (.005)**	.015 (.005)**	.015 (.005)**	.015 (.005)**	.000 (.004)	.000 (.003)
W2 ID-FT covariance		.002 (.002)	.002 (.002)	.002 (.002)	.002 (.002)	-.000 (.007)	.007 (.008)
W3 ID-FT covariance		.003 (.002)	.003 (.002)	.003 (.002)	.003 (.002)	.001 (.003)	.002 (.003)
CFI		.926	.927	.945	.944	1.000	.995
RMSEA		.203	.143	.200	.143	.030	.047
SRMR		.044	.050	.023	.026	.015	.034
Chisq (df)		48.932 (4)***	52.460 (8)***	47.623 (4)***	52.448 (8)***	1.252 (1)	7.957 (5)
Chisq test			3.528 (4)		4.825 (4)		6.705 (4)

Note: N = 272 for all models.

Table A29

Study 2 POC Identity & Nonwhite FT Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
POC	ID	.766	.791	.734	.766	.136	.179
ID	w1	(.029)***	(.021)***	(.029)***	(.022)***	(.166)	(.158)
w2	FT	.089	.040	.079	.038	.162	.040
	w1	(.030)**	(.023)$^{+}$	(.031)*	(.023)$^{+}$	(.154)	(.127)
FT	ID	.032	.053	.038	.056	-.140	.033
w2	w1	(.025)	(.019)**	(.026)	(.019)**	(.114)	(.096)
	FT	.761	.788	.759	.784	-.027	.034
	w1	(.026)***	(.020)***	(.027)***	(.020)***	(.141)	(.132)
POC	ID	.820	.791	.805	.766	.308	.179
ID	w2	(.030)***	(.021)***	(.032)***	(.022)***	(.108)**	(.158)
w3	FT	-.016	.040	-.012	.038	-.164	.040
	w2	(.033)	(.023)$^{+}$	(.033)	(.023)$^{+}$	(.145)	(.127)
FT	ID	.080	.053	.078	.056	.174	.033
w3	w2	(.028)**	(.019)**	(.030)**	(.019)**	(.111)	(.096)
	FT	.825	.788	.819	.784	.033	.034
	w2	(.031)***	(.020)***	(.031)***	(.020)***	(.164)	(.132)
ID-FT trait						.013	.013
covariance						(.003)***	(.003)***
W1 ID-FT		.012	.012	.012	.012	-.002	-.001
covariance		(.003)***	(.003)***	(.003)***	(.003)***	(.002)	(.001)
W2 ID-FT		.001	.001	.001	.001	.001	.001
covariance		(.001)	(.001)	(.001)	(.001)	(.003)	(.003)
W3 ID-FT		.001	.001	.001	.001	.000	.000
covariance		(.001)	(.001)	(.001)	(.001)	(.002)	(.001)
CFI		.947	.943	.955	.953	.999	.997
RMSEA		.201	.147	.201	.146	.046	.042
SRMR		.035	.042	.018	.021	.011	.023
Chisq (df)		110.739	122.035	110.861	120.373	2.399 (1)	10.708
		(4)***	(8)***	(4)***	(8)***		(5)$^{+}$
Chisq test			11.296		9.512		8.309
			(4)*		(4)*		(4)$^{+}$

Note: N = 658 for all models.

Table A30

Study 2 POC Identity & Nonwhite FT Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
POC ID w2	ID w1	.660 (.053)***	.708 (.044)***	.635 (.057)***	.677 (.047)***	-.193 (.152)	-.390 (.159)*
	FT w1	.015 (.072)	.040 (.057)	-.067 (.076)	-.014 (.062)	-.276 (.386)	-.050 (.176)
FT w2	ID w1	.067 (.045)	.028 (.032)	.096 (.049)*	.052 (.035)	.300 (.215)	.055 (.094)
	FT w1	.733 (.061)***	.795 (.042)***	.682 (.066)***	.762 (.045)***	-.810 (.701)	-.386 (.179)*
POC ID w3	ID w2	.804 (.073)***	.708 (.044)***	.776 (.081)***	.677 (.047)***	-.817 (.562)	-.390 (.159)*
	FT w2	.074 (.091)	.040 (.057)	.086 (.100)	-.014 (.062)	.103 (.398)	-.050 (.176)
FT w3	ID w2	-.008 (.045)	.028 (.032)	.017 (.049)	.052 (.035)	-.272 (.261)	.055 (.094)
	FT w2	.848 (.056)***	.795 (.042)***	.830 (.060)***	.762 (.045)***	.163 (.190)	-.386 (.179)*
ID-FT trait covariance						.020 (.005)***	.021 (.005)***
W1 ID-FT covariance		.024 (.005)***	.024 (.005)***	.024 (.005)***	.024 (.005)***	.004 (.004)	.001 (.002)
W2 ID-FT covariance		.003 (.003)	.003 (.003)	.003 (.003)	.003 (.003)	.000 (.005)	.002 (.005)
W3 ID-FT covariance		.003 (.003)	.003 (.003)	.003 (.003)	.004 (.003)	-.002 (.004)	-.001 (.004)
CFI		.854	.849	.898	.893	1.000	.993
RMSEA		.272	.195	.267	.194	.000	.052
SRMR		.063	.076	.032	.039	.009	.042
Chisq (df)		84.382 (4)***	90.641 (8)***	81.765 (4)***	89.620 (8)***	0.412 (1)	8.617 (5)
Chisq test			6.259 (4)		7.855 (4)$^{+}$		8.205 (4)$^{+}$

Note: N = 272 for all models

Table A31

Study 2 American Identity & Nonwhite FT Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
Am. ID w2	ID w1	.744 (.025)***	.780 (.019)***	.746 (.027)***	.767 (.019)***	-.029 (.099)	-.091 (.093)
	FT w1	.002 (.031)	.017 (.022)	.008 (.031)	.029 (.022)	-.151 (.106)	-.223 (.090)*
FT w2	ID w1	.032 (.022)	.056 (.017)**	.045 (.023)$^{+}$	.061 (.018)***	-.144 (.087)$^{+}$	-.124 (.071)$^{+}$
	FT w1	.759 (.026)***	.785 (.020)***	.753 (.027)***	.780 (.021)***	.022 (.123)	.007 (.121)
Am. ID w3	ID w2	.826 (.027)***	.780 (.019)***	.793 (.028)***	.767 (.019)***	-.250 (.250)	-.091 (.093)
	FT w2	.042 (.032)	.017 (.022)	.054 (.032)$^{+}$	.029 (.022)	-.443 (.273)	-.223 (.090)*
FT w3	ID w2	.096 (.026)***	.056 (.017)**	.087 (.027)**	.061 (.018)***	-.138 (.182)	-.124 (.071)$^{+}$
	FT w2	.825 (.031)***	.785 (.020)***	.817 (.031)***	.780 (.021)***	-.074 (.217)	.007 (.121)
ID-FT trait covariance						.017 (.003)***	.017 (.003)***
W1 ID-FT covariance		.016 (.003)***	.016 (.003)***	.016 (.003)***	.016 (.003)***	-.000 (.002)	-.001 (.001)
W2 ID-FT covariance		.000 (.001)	.001 (.001)	.000 (.001)	.001 (.001)	-.005 (.002)*	-.004 (.002)*
W3 ID-FT covariance		.003 (.001)*	.003 (.001)*	.002 (.001)*	.002 (.001)*	.001 (.002)	.002 (.001)
CFI		.930	.926	.946	.945	.997	.998
RMSEA		.241	.175	.229	.164	.101	.035
SRMR		.039	.050	.018	.022	.021	.022
Chisq (df)		156.572 (4)***	169.483 (8)***	142.475 (4)***	149.719 (8)***	7.740 (1)**	9.115 (5)
Chisq test			12.911 (4)*		7.244 (4)		1.375 (4)

Note: N = 658 for all models.

Table A32

Study 2 American Identity & Nonwhite FT Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
Am. ID w2	ID w1	.766 (.043)***	.858 (.033)***	.700 (.048)***	.796 (.037)***	-.195 (.290)	-.385 (.167)*
	FT w1	-.064 (.048)	-.043 (.035)	-.077 (.051)	-.065 (.037)$^{+}$	-.597 (.378)	-.211 (.118)$^{+}$
FT w2	ID w1	.158 (.051)**	.054 (.037)	.181 (.058)**	.034 (.044)	.599 (.281)*	.103 (.156)
	FT w1	.742 (.057)***	.794 (.040)***	.705 (.062)***	.775 (.044)***	-.386 (.460)	-.351 (.181)$^{+}$
Am. ID w3	ID w2	.945 (.046)***	.858 (.033)***	.883 (.051)***	.796 (.037)***	-.198 (.435)	-.385 (.167)*
	FT w2	-.013 (.049)	-.043 (.035)	-.046 (.053)	-.065 (.037)$^{+}$	.292 (.266)	-.211 (.118)$^{+}$
FT w3	ID w2	-.024 (.050)	.054 (.037)	-.087 (.056)	.034 (.044)	-.387 (.304)	.103 (.156)
	FT w2	.848 (.054)***	.794 (.040)***	.845 (.058)***	.775 (.044)***	.275 (.200)	-.351 (.181)$^{+}$
ID-FT trait covariance						.003 (.004)	.004 (.004)
W1 ID-FT covariance		.001 (.004)	.001 (.004)	.001 (.004)	.001 (.004)	-.002 (.003)	-.003 (.002)$^{+}$
W2 ID-FT covariance		-.001 (.002)	-.001 (.002)	-.000 (.002)	-.001 (.002)	.003 (.004)	.000 (.003)
W3 ID-FT covariance		.004 (.002)*	.003 (.002)$^{+}$	.003 (.002)$^{+}$	.002 (.002)	.002 (.002)	.001 (.003)
CFI		.896	.875	.924	.906	1.000	.993
RMSEA		.254	.197	.255	.201	.000	.061
SRMR		.050	.076	.027	.037	.004	.045
Chisq (df)		74.348 (4)***	92.128 (8)***	74.964 (4)***	95.622 (8)***	0.110 (1)	10.015 (5)$^{+}$
Chisq test			17.780 (4)**		20.658 (4)***		9.905 (4)*

Note: N = 272 for all models.

Table A33

Study 2 Racial Identity & White FT Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
racial ID w2	ID w1	.770 (.028)***	.791 (.021)***	.746 (.029)***	.769 (.022)***	-.077 (.152)	-.019 (.129)
	FT w1	.005 (.027)	-.016 (.019)	.007 (.027)	-.019 (.020)	.014 (.103)	.049 (.069)
FT w2	ID w1	.053 (.034)	.056 (.024)*	.034 (.035)	.046 (.025)$^{+}$	.125 (.170)	.225 (.102)*
	FT w1	.709 (.033)***	.718 (.023)***	.695 (.033)***	.699 (.023)***	-.013 (.143)	.097 (.105)
racial ID w3	ID w2	.817 (.031)***	.791 (.021)***	.797 (.032)***	.769 (.022)***	.018 (.146)	-.019 (.129)
	FT w2	-.040 (.028)	-.016 (.019)	-.048 (.028)$^{+}$	-.019 (.020)	.009 (.101)	.049 (.069)
FT w3	ID w2	.057 (.035)	.056 (.024)*	.058 (.037)	.046 (.025)$^{+}$	.226 (.138)	.225 (.102)*
	FT w2	.728 (.032)***	.718 (.023)***	.703 (.033)***	.699 (.023)***	.119 (.103)	.097 (.105)
ID-FT trait covariance						.002 (.003)	.001 (.003)
W1 ID-FT covariance		.001 (.003)	.001 (.003)	.001 (.003)	.001 (.003)	-.001 (.002)	.000 (.001)
W2 ID-FT covariance		.002 (.001)	.002 (.001)	.001 (.001)	.001 (.001)	.004 (.003)	.005 (.003)$^{+}$
W3 ID-FT covariance		-.000 (.001)	-.000 (.001)	-.000 (.001)	-.000 (.001)	.001 (.002)	.000 (.001)
CFI		.910	.910	.928	.929	.999	1.000
RMSEA		.243	.171	.240	.169	.055	.000
SRMR		.049	.051	.025	.026	.013	.018
Chisq (df)		160.023 (4)***	162.826 (8)***	155.486 (4)***	159.025 (8)***	2.958 (1)$^{+}$	4.828 (5)
Chisq test			2.803 (4)		3.539 (4)		1.870 (4)

Note: N = 658 for all models.

Table A34

Study 2 Racial Identity & White FT Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
racial ID w2	ID w1	.806 (.046)***	.844 (.035)***	.795 (.047)***	.837 (.036)***	.052 (.391)	-.012 (.320)
	FT w1	-.006 (.048)	-.030 (.037)	-.026 (.053)	-.064 (.041)	-.067 (.169)	-.068 (.207)
FT w2	ID w1	-.032 (.054)	-.023 (.038)	-.029 (.053)	-.020 (.038)	-.269 (.298)	-.104 (.334)
	FT w1	.645 (.057)***	.698 (.041)***	.603 (.059)***	.648 (.044)***	.155 (.194)	.180 (.294)
racial ID w3	ID w2	.899 (.054)***	.844 (.035)***	.896 (.057)***	.837 (.036)***	.303 (.298)	-.012 (.320)
	FT w2	-.048 (.059)	-.030 (.037)	-.104 (.066)	-.064 (.041)	-.268 (.204)	-.068 (.207)
FT w3	ID w2	.002 (.055)	-.023 (.038)	.007 (.056)	-.020 (.038)	-.205 (.253)	-.104 (.334)
	FT w2	.747 (.059)***	.698 (.041)***	.692 (.066)***	.648 (.044)***	.278 (.200)	.180 (.294)
ID-FT trait covariance						.007 (.006)	.005 (.007)
W1 ID-FT covariance		.006 (.005)	.006 (.005)	.006 (.005)	.006 (.005)	-.000 (.005)	-.001 (.004)
W2 ID-FT covariance		.002 (.003)	.002 (.003)	.002 (.002)	.002 (.002)	-.003 (.005)	.001 (.008)
W3 ID-FT covariance		.009 (.003)**	.009 (.003)**	.008 (.003)**	.008 (.003)**	.005 (.003)	.006 (.003)**
CFI		.973	.973	.982	.982	1.000	1.000
RMSEA		.114	.081	.108	.077	.000	.000
SRMR		.032	.044	.015	.020	.004	.025
Chisq (df)		18.263 (4)**	22.194 (8)**	16.657 (4)**	20.826 (8)**	0.060 (1)	3.858 (5)
Chisq test			3.931 (4)		4.169 (4)		3.798 (4)

Note: N = 272 for all models.

Table A35

Study 2 POC Identity & White FT Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
POC ID w2	ID w1	.781 (.028)***	.799 (.021)***	.744 (.029)***	.772 (.021)***	.079 (.173)	.239 (.135)$^{+}$
	FT w1	-.019 (.028)	-.026 (.020)	-.021 (.028)	-.028 (.020)	-.075 (.119)	.000 (.080)
FT w2	ID w1	.072 (.033)*	.058 (.023)*	.051 (.034)	.045 (.025)$^{+}$	.143 (.158)	.138 (.105)
	FT w1	.706 (.033)***	.716 (.023)***	.693 (.033)***	.697 (.023)***	-.001 (.142)	.085 (.112)
POC ID w3	ID w2	.820 (.030)***	.799 (.021)***	.805 (.031)***	.772 (.021)***	.272 (.110)*	.239 (.135)$^{+}$
	FT w2	-.034 (.028)	-.026 (.020)	-.037 (.029)	-.028 (.020)	-.009 (.086)	.000 (.080)
FT w3	ID w2	.040 (.034)	.058 (.023)*	.034 (.036)	.045 (.025)$^{+}$	.051 (.118)	.138 (.105)
	FT w2	.728 (.032)***	.716 (.023)***	.703 (.033)***	.697 (.023)***	.137 (.101)	.085 (.112)
ID-FT trait covariance						.004 (.003)	.004 (.003)
W1 ID-FT covariance		.004 (.003)	.004 (.003)	.004 (.003)	.004 (.003)	-.001 (.002)	-.000 (.002)
W2 ID-FT covariance		.003 (.002)	.002 (.002)	.002 (.001)	.002 (.002)	.003 (.003)	.004 (.003)
W3 ID-FT covariance		-.001 (.001)	-.001 (.001)	-.001 (.001)	-.001 (.001)	-.002 (.002)	-.001 (.001)
CFI		.928	.929	.941	.942	.998	.998
RMSEA		.217	.152	.217	.152	.079	.034
SRMR		.045	.046	.023	.024	.016	.022
Chisq (df)		128.456 (4)***	130.135 (8)***	127.746 (4)***	130.038 (8)***	5.110 (1)*	8.861 (5)
Chisq test			1.679 (4)		2.292 (4)		3.751 (4)

Note: N = 658 for all models.

Table A36

Study 2 POC Identity & White FT Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
POC ID w2	ID w1	.664 (.051)***	.718 (.042)***	.620 (.054)***	.676 (.045)***	-.290 (.159)⁺	-.434 (.159)**
	FT w1	-.005 (.063)	-.003 (.051)	-.047 (.067)	-.033 (.055)	-.120 (.129)	-.127 (.143)
FT w2	ID w1	.005 (.046)	-.004 (.034)	.046 (.047)	.031 (.036)	-.014 (.199)	-.045 (.117)
	FT w1	.643 (.057)***	.692 (.041)***	.599 (.059)***	.641 (.044)***	.129 (.205)	.157 (.209)
POC ID w3	ID w2	.823 (.070)***	.718 (.042)***	.796 (.080)***	.676 (.045)***	-.867 (.590)	-.434 (.159)**
	FT w2	.012 (.084)	-.003 (.051)	.013 (.095)	-.033 (.055)	.030 (.442)	-.127 (.143)
FT w3	ID w2	-.006 (.050)	-.004 (.034)	.024 (.055)	.031 (.036)	-.016 (.230)	-.045 (.117)
	FT w2	.747 (.059)***	.692 (.041)***	.695 (.066)***	.641 (.044)***	.280 (.194)	.157 (.209)
ID-FT trait covariance						-.001 (.005)	-.001 (.005)
W1 ID-FT covariance		-.004 (.006)	-.004 (.006)	-.004 (.006)	-.004 (.006)	-.004 (.004)	-.003 (.003)
W2 ID-FT covariance		-.001 (.003)	-.001 (.003)	.000 (.003)	.000 (.003)	-.001 (.007)	-.003 (.005)
W3 ID-FT covariance		.004 (.004)	.004 (.004)	.005 (.003)	.005 (.004)	.005 (.004)	.004 (.003)
CFI		.883	.881	.927	.926	1.000	1.000
RMSEA		.218	.156	.212	.151	.000	.000
SRMR		.056	.070	.028	.035	.003	.024
Chisq (df)		55.533 (4)***	60.618 (8)***	52.839 (4)***	57.704 (8)***	0.045 (1)	2.221 (5)
Chisq test			5.085 (4)		4.865 (4)		2.176 (4)

Note: N = 272 for all models.

Table A37

Study 2 American Identity & White FT Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
Am. ID w2	ID w1	.739 (.026)***	.774 (.019)***	.741 (.027)***	.764 (.020)***	-.068 (.086)	-.080 (.096)
	FT w1	.019 (.029)	.035 (.021)+	.024 (.030)	.031 (.021)	-.070 (.076)	-.066 (.070)
FT w2	ID w1	.119 (.030)***	.103 (.022)***	.115 (.031)***	.097 (.023)***	.170 (.131)	-.004 (.097)
	FT w1	.667 (.034)***	.684 (.024)***	.659 (.034)***	.670 (.024)***	.018 (.131)	.076 (.112)
Am. ID w3	ID w2	.815 (.028)***	.774 (.019)***	.789 (.029)***	.764 (.020)***	-.257 (.226)	-.080 (.096)
	FT w2	.051 (.029)+	.035 (.021)+	.037 (.029)	.031 (.021)	.008 (.122)	-.066 (.070)
FT w3	ID w2	.087 (.033)**	.103 (.022)***	.077 (.033)*	.097 (.023)***	-.190 (.170)	-.004 (.097)
	FT w2	.702 (.034)***	.103 (.022)***	.682 (.034)***	.670 (.024)***	.153 (.103)	.076 (.112)
ID-FT trait covariance						.023 (.003)***	.024 (.003)***
W1 ID-FT covariance		.026 (.003)***	.026 (.003)***	.026 (.003)***	.026 (.003)***	.003 (.002)	.001 (.001)
W2 ID-FT covariance		.002 (.002)	.002 (.002)	.002 (.001)	.002 (.001)	.001 (.003)	-.001 (.003)
W3 ID-FT covariance		.004 (.001)**	.004 (.001)*	.003 (.001)*	.003 (.001)*	-.000 (.002)	.001 (.001)
CFI		.918	.916	.936	.936	.999	.999
RMSEA		.247	.177	.239	.168	.052	.029
SRMR		.047	.051	.023	.024	.013	.021
Chisq (df)		164.981 (4)***	172.008 (8)***	154.244 (4)***	157.196 (8)***	2.750 (1)+	7.677 (5)
Chisq test			7.027(4)		2.952 (4)		4.927 (4)

Note: N = 658 for all models.

Table A38

Study 2 American Identity & White FT Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
Am. ID w2	ID w1	.747 (.044)***	.842 (.035)***	.690 (.048)***	.789 (.038)***	-.086 (.242)	-.372 (.172)*
	FT w1	.052 (.046)	.041 (.035)	.028 (.048)	.008 (.036)	-.022 (.108)	-.099 (.093)
FT w2	ID w1	.226 (.053)***	.121 (.043)**	.244 (.057)***	.112 (.048)*	.581 (.236)*	-.164 (.168)
	FT w1	.579 (.055)***	.646 (.043)***	.570 (.056)***	.615 (.045)***	.174 (.157)	-.040 (.146)
Am. ID w3	ID w2	.931 (.049)***	.842 (.035)***	.885 (.054)***	.789 (.038)***	-.420 (.573)	-.372 (.172)*
	FT w2	.031 (.051)	.041 (.035)	-.026 (.054)	.008 (.036)	.500 (.321)	-.099 (.093)
FT w3	ID w2	.003 (.063)	.121 (.043)**	-.068 (.070)	.112 (.048)*	-.884 (.485)$^{+}$	-.164 (.168)
	FT w2	.746 (.065)***	.646 (.043)***	.715 (.070)***	.615 (.045)***	.621 (.294)*	-.040 (.146)
ID-FT trait covariance						.017 (.005)**	.022 (.004)***
W1 ID-FT covariance		.015 (.005)**	.015 (.005)**	.015 (.005)**	.015 (.005)**	-.001 (.004)	-.006 (.002)*
W2 ID-FT covariance		.001 (.002)	.001 (.002)	.001 (.002)	.000 (.002)	.008 (.004)*	-.001 (.003)
W3 ID-FT covariance		.006 (.002)**	.006 (.002)**	.005 (.002)**	.004 (.002)*	.003 (.003)	.004 (.002)
CFI		.938	.913	.956	.934	1.000	.994
RMSEA		.187	.157	.187	.161	.000	.052
SRMR		.041	.071	.020	.033	.008	.040
Chisq (df)		42.039 (4)***	61.403 (8)***	42.159 (4)***	64.726 (8)***	0.309 (1)	8.657 (5)
Chisq test			19.364 (4)***		22.567 (4)***		8.348 (4)$^{+}$

Note: N = 272 for all models.

Table A39

Study 2 Racial Identity & Immigration Attitudes (number of immigrants) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
racial ID w2	ID w1	.756 (.028)***	.776 (.021)***	.737 (.29)***	.757 (.022)***	-.134 (.158)	-.083 (.133)
	immig 1 w1	.081 (.029)**	.082 (.021)***	.068 (.030)*	.076 (.022)***	.048 (.111)	.092 (.090)
immig 1 w2	ID w1	.021 (.032)	.049 (.024)*	.012 (.033)	.030 (.024)	-.213 (.171)	-.029 (.121)
	immig 1 w1	.678 (.033)***	.676 (.024)***	.658 (.034)***	.654 (.025)***	-.091 (.142)	-.029 (.120)
racial ID w3	ID w2	.799 (.031)***	.776 (.021)***	.781 (.032)***	.757 (.022)***	-.017 (.145)	-.083 (.133)
	immig 1 w2	.082 (.031)**	.082 (.021)***	.086 (.032)**	.076 (.022)***	.122 (.107)	.092 (.090)
immig 1 w3	ID w2	.080 (.035)*	.049 (.024)*	.051 (.036)	.030 (.024)	.160 (.129)	-.029 (.121)
	immig 1 w2	.673 (.035)***	.676 (.024)***	.649 (.036)***	.654 (.025)***	.019 (.103)	-.029 (.120)
ID-attitude trait covariance						.014 (.003)***	.013 (.003)***
W1 ID-attitude covariance		.013 (.003)***	.013 (.003)***	.013 (.003)***	.013 (.003)***	-.001 (.002)	.002 (.001)
W2 ID-attitude covariance		.003 (.001)*	.003 (.001)*	.002 (.001)$^{+}$	.002 (.001)$^{+}$	-.000 (.003)	.000 (.003)
W3 ID-attitude covariance		-.000 (.001)	-.000 (.001)	-.000 (.001)	-.000 (.001)	.002 (.002)	-.000 (.001)
CFI		.899	.900	.921	.922	1.000	1.000
RMSEA		.256	.180	.252	.177	.000	.012
SRMR		.055	.056	.027	.028	.005	.017

Chisq (df)	176.318 (4)***	178.936 (8)***	171.106 (4)***	173.075 (8)***	0.367 (1)	5.466 (5)
Chisq test		2.618 (4)		1.969 (4)		5.079 (4)

Note: N = 658 for all models.

Table A40

Study 2 Racial Identity & Immigration Attitudes (number of immigrants) Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat[a]**
racial ID w2	ID w1	.788 (.047)***	.840 (.036)***	.778 (.048)***	.833 (.037)***	-.913 (1.402)	-.128 (.221)
	immig1 w1	.078 (.050)	.007 (.038)	.074 (.058)	-.005 (.044)	1.253 (1.215)	.263 (.115)*
immig1 w2	ID w1	-.009 (.060)	-.022 (.038)	-.003 (.059)	-.016 (.037)	.814 (1.068)	.330 (.168)*
	immig1 w1	.677 (.064)***	.768 (.039)***	.547 (.072)***	.708 (.044)***	-.957 (1.055)	-.272 (.140)$^+$
racial ID w3	ID w2	.904 (.055)***	.840 (.036)***	.898 (.057)***	.833 (.037)***	.242 (.303)	-.128 (.221)
	immig1 w2	-.057 (.054)	.007 (.038)	-.051 (.065)	-.005 (.044)	-.207 (.220)	.263 (.115)*
immig1 w3	ID w2	-.013 (.049)	-.022 (.038)	.007 (.047)	-.016 (.037)	-.009 (.290)	.330 (.168)*
	immig1 w2	.809 (.049)***	.768 (.039)***	.787 (.053)***	.708 (.044)***	.098 (.198)	-.272 (.140)$^+$
ID-attitude trait covariance						.007 (.005)	.009 (.005)$^+$
W1 ID-attitude covariance		.016 (.005)**	.016 (.005)**	.016 (.005)**	.016 (.005)**	.009 (.004)*	.002 (.003)
W2 ID-attitude covariance		-.003 (.003)	-.003 (.003)	-.004 (.003)	-.004 (.003)$^+$	.015 (.018)	.009 (.004)*
W3 ID-attitude covariance		.003 (.002)	.003 (.002)	.003 (.002)	.003 (.002)	-.001 (.003)	-.001 (.003)
CFI		.908	.901	.931	.922	1.000	.991
RMSEA		.226	.165	.233	.175	.000	.064
SRMR		.049	.061	.025	.033	.003	.046
Chisq (df)		59.708 (4)***	67.460 (8)***	63.172 (4)***	74.619 (8)***	0.049 (1)	10.488 (5)$^+$
Chisq test			7.752 (4)		11.447 (4)*		10.439 (4)*

Note: N = 272 for all models.

Table A41

Study 2 Racial Identity & Immigration Attitudes (ending criminal penalties) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
racial ID w2	ID w1	.771 (.028)***	.788 (.021)***	.749 (.029)***	.767 (.022)***	-.110 (.153)	-.082 (.127)
	immig2 w1	-.010 (.025)	.017 (.018)	-.018 (.025)	.013 (.018)	-.053 (.041)	-.025 (.032)
immig2 w2	ID w1	.057 (.050)	.056 (.037)	.051 (.052)	.047 (.039)	-.024 (.260)	-.086 (.137)
	immig2 w1	.276 (.044)***	.283 (.032)***	.275 (.044)***	.285 (.032)***	-.048 (.084)	-.026 (.069)
racial ID w3	ID w2	.809 (.031)***	.788 (.021)***	.791 (.032)***	.767 (.022)***	.006 (.146)	-.082 (.127)
	immig2 w2	.046 (.025)+	.017 (.018)	.045 (.025)+	.013 (.018)	.025 (.057)	-.025 (.032)
immig2 w3	ID w2	.057 (.055)	.056 (.037)	.045 (.058)	.047 (.039)	.038 (.172)	-.086 (.137)
	immig2 w2	.292 (.045)***	.283 (.032)***	.299 (.045)***	.285 (.032)***	.006 (.075)	-.026 (.069)
ID-attitude trait covariance						.007 (.003)*	.007 (.003)**
W1 ID-attitude covariance		.008 (.003)*	.008 (.003)*	.008 (.003)*	.008 (.003)*	-.000 (.002)	.001 (.002)
W2 ID-attitude covariance		.002 (.002)	.002 (.002)	.002 (.002)	.002 (.002)	-.000 (.004)	-.002 (.003)
W3 ID-attitude covariance		.004 (.002)+	.004 (.002)+	.004 (.002)+	.004 (.002)+	.004 (.002)+	.003 (.002)
CFI		.901	.901	.926	.925	1.000	1.000
RMSEA		.203	.143	.203	.144	.019	.000
SRMR		.054	.055	.028	.028	.013	.015
Chisq (df)		112.131 (4)***	115.836 (8)***	112.127 (4)***	116.768 (8)***	1.237 (1)	3.867 (5)
Chisq test			3.705 (4)		4.641 (4)		2.630 (4)

Note: N = 658 for all models.

Table A42

Study 2 Racial Identity & Immigration Attitudes (ending criminal penalties) Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
racial ID w2	ID w1	.805 (.045)***	.847 (.035)***	.793 (.047)***	.838 (.036)***	-.213 (.520)	-.112 (.239)
	immig 2 w1	.021 (.042)	.019 (.030)	.015 (.043)	.024 (.032)	-.040 (.107)	-.028 (.066)
immig 2 w2	ID w1	-.001 (.087)	.051 (.067)	-.006 (.083)	.029 (.067)	-.572 (.654)	-.377 (.311)
	immig 2 w1	.373 (.080)***	.391 (.059)***	.303 (.076)***	.334 (.059)***	.019 (.176)	.074 (.143)
racial ID w3	ID w2	.897 (.054)***	.847 (.035)***	.898 (.057)***	.838 (.036)***	.281 (.303)	-.112 (.239)
	immig 2 w2	.014 (.045)	.019 (.030)	.031 (.048)	.024 (.032)	-.026 (.101)	-.028 (.066)
immig 2 w3	ID w2	.098 (.106)	.051 (.067)	.061 (.111)	.029 (.067)	-.301 (.434)	-.377 (.311)
	immig 2 w2	.415 (.087)***	.391 (.059)***	.376 (.093)***	.334 (.059)***	.106 (.158)	.074 (.143)
ID-attitude trait covariance						.009 (.007)	.009 (.006)
W1 ID-attitude covariance		.005 (.006)	.005 (.006)	.005 (.006)	.005 (.006)	-.003 (.006)	-.002 (.005)
W2 ID-attitude covariance		.002 (.004)	.002 (.004)	.002 (.004)	.002 (.004)	-.007 (.010)	-.005 (.007)
W3 ID-attitude covariance		-.011 (.005)*	-.011 (.005)*	-.010 (.005)*	-.010 (.005)*	-.013 (.005)**	-.014 (.005)**
CFI		.952	.956	.966	.968	1.000	1.000
RMSEA		.127	.086	.129	.089	.000	.000
SRMR		.042	.050	.022	.026	.019	.025
Chisq (df)		21.439 (4)***	23.974 (8)**	22.137 (4)***	25.067 (8)**	0.644 (1)	2.035 (5)
Chisq test			2.535 (4)		2.930 (4)		1.391 (4)

Note: N = 272 for all models.

Table A43

Study 2 POC Identity & Immigration Attitudes (number of immigrants) Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
POC ID w2	ID w1	.762 (.029)***	.786 (.021)***	.731 (.030)***	.763 (.022)***	.080 (.161)	.207 (.127)
	immig 1 w1	.101 (.031)**	.065 (.022)**	.084 (.031)**	.058 (.023)*	.140 (.120)	.079 (.077)
immig 1 w2	ID w1	.034 (.031)	.072 (.023)**	.030 (.032)	.058 (.024)*	-.084 (.146)	.158 (.093)$^{+}$
	immig 1 w1	.675 (.033)***	.669 (.024)***	.654 (.034)***	.647 (.025)***	-.056 (.138)	.017 (.101)
POC ID w3	ID w2	.812 (.030)***	.786 (.021)***	.799 (.032)***	.763 (.022)***	.267 (.109)*	.207 (.127)
	immig 1 w2	.025 (.032)	.065 (.022)**	.027 (.033)	.058 (.023)*	-.039 (.091)	.079 (.077)
immig 1 w3	ID w2	.111 (.033)**	.072 (.023)**	.087 (.035)*	.058 (.024)*	.298 (.110)**	.158 (.093)$^{+}$
	immig 1 w2	.665 (.035)***	.669 (.024)***	.640 (.036)***	.647 (.025)***	.027 (.102)	.017 (.101)
ID-attitude trait covariance						.014 (.003)***	.014 (.003)***
W1 ID-attitude covariance		.015 (.003)***	.015 (.003)***	.015 (.003)***	.015 (.003)***	.000 (.002)	.001 (.002)
W2 ID-attitude covariance		.003 (.001)$^{+}$	.003 (.001)$^{+}$	.002 (.001)	.002 (.001)	.002 (.003)	.004 (.003)
W3 ID-attitude covariance		.000 (.001)	.000 (.001)	.000 (.001)	.000 (.001)	.001 (.002)	.001 (.001)
CFI		.921	.919	.936	.936	1.000	.998
RMSEA		.226	.161	.226	.160	.000	.031
SRMR		.050	.053	.025	.026	.007	.023
Chisq (df)		138.417 (4)***	144.891 (8)***	138.103 (4)***	142.769 (8)***	0.881 (1)	8.258 (5)
Chisq test			6.474 (4)		4.666 (4)		7.377 (4)

Note: N = 658 for all models.

Table A44

Study 2 POC Identity & Immigration Attitudes (number of immigrants) Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
POC ID w2	ID w1	.612 (.052)***	.674 (.044)***	.589 (.053)***	.654 (.045)***	-.244 (.126)$^{+}$	-.405 (.156)**
	immig1 w1	.187 (.067)**	.152 (.052)**	.217 (.072)**	.153 (.059)**	.199 (.246)	.158 (.134)
immig1 w2	ID w1	.105 (.051)*	.051 (.035)	.063 (.052)	.032 (.035)	.141 (.175)	.038 (.095)
	immig1 w1	.628 (.065)***	.736 (.041)***	.529 (.070)***	.694 (.045)***	-.592 (.303)$^{+}$	-.320 (.128)*
POC ID w3	ID w2	.786 (.074)***	.674 (.044)***	.790 (.080)***	.654 (.045)***	-.934 (.666)	-.405 (.156)**
	immig1 w2	.116 (.081)	.152 (.052)**	.084 (.093)	.153 (.059)**	-.137 (.454)	.158 (.134)
immig1 w3	ID w2	.021 (.047)	.051 (.035)	.026 (.046)	.032 (.035)	-.281 (.327)	.038 (.095)
	immig1 w2	.800 (.051)***	.736 (.041)***	.783 (.054)***	.694 (.045)***	.049 (.222)	-.320 (.128)*
ID-attitude trait covariance						.027 (.005)***	.027 (.005)***
W1 ID-attitude covariance		.028 (.006)***	.028 (.006)***	.028 (.006)***	.028 (.006)***	.001 (.004)	-.002 (.002)
W2 ID-attitude covariance		-.002 (.003)	-.003 (.003)	-.003 (.003)	-.003 (.003)	.000 (.005)	.003 (.005)
W3 ID-attitude covariance		.004 (.003)	.003 (.003)	.003 (.003)	.003 (.003)	-.003 (.005)	-.000 (.003)
CFI		.850	.843	.893	.882	1.000	.994
RMSEA		.275	.200	.284	.211	.009	.050
SRMR		.065	.077	.033	.042	.014	.041
Chisq (df)		86.495 (4)***	94.760 (8)***	91.805 (4)***	104.929 (8)***	1.020 (1)	8.447 (5)
Chisq test			8.265 (4)$^{+}$		13.124 (4)*		7.427 (4)

Note: N = 272 for all models.

Table A45

Study 2 POC Identity & Immigration Attitudes (ending criminal penalties) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
POC ID w2	ID w1	.779 (.029)***	.795 (.021)***	.745 (.030)***	.770 (.022)***	.084 (.167)	.221 (.139)
	immig2 w1	.005 (.026)	.020 (.018)	-.005 (.026)	.015 (.018)	.004 (.046)	.010 (.034)
immig2 w2	ID w1	.031 (.048)	.051 (.036)	.020 (.051)	.043 (.037)	-.071 (.227)	-.029 (.132)
	immig2 w1	.279 (.044)***	.284 (.032)***	.277 (.044)***	.287 (.032)***	-.044 (.084)	-.020 (.069)
POC ID w3	ID w2	.814 (.030)***	.795 (.021)***	.801 (.031)***	.770 (.022)***	.263 (.109)*	.221 (.139)
	immig2 w2	.035 (.025)	.020 (.018)	.035 (.026)	.015 (.018)	.019 (.048)	.010 (.034)
immig2 w3	ID w2	.075 (.052)	.051 (.036)	.071 (.055)	.043 (.037)	.024 (.147)	-.029 (.132)
	immig2 w2	.291 (.045)***	.284 (.032)***	.298 (.045)***	.287 (.032)***	.003 (.075)	-.020 (.069)
ID-attitude trait covariance						.006 (.003)*	.006 (.003)*
W1 ID-attitude covariance		.008 (.003)*	.008 (.003)*	.008 (.003)*	.008 (.003)*	.002 (.003)	.002 (.002)
W2 ID-attitude covariance		.002 (.002)	.002 (.002)	.001 (.002)	.001 (.002)	-.000 (.004)	-.000 (.003)
W3 ID-attitude covariance		.003 (.002)	.003 (.002)	.002 (.002)	.002 (.002)	.002 (.002)	.002 (.002)
CFI		.931	.933	.946	.946	1.000	1.000
RMSEA		.167	.116	.172	.122	.000	.000
SRMR		.049	.050	.026	.026	.002	.013
Chisq (df)		77.277 (4)***	79.217 (8)***	82.186 (4)***	85.900 (8)***	0.057 (1)	2.736 (5)
Chisq test			1.940 (4)		3.714 (4)		2.679 (4)

Note: N = 658 for all models.

Table A46

Study 2 POC Identity & Immigration Attitudes (ending criminal penalties) Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
POC ID w2	ID w1	.662 (.051)***	.714 (.042)***	.620 (.054)***	.675 (.046)***	-.246 (.126)+	-.363 (.172)*
	immig2 w1	.024 (.055)	.028 (.042)	.027 (.055)	.017 (.043)	.043 (.056)	.099 (.078)
immig2 w2	ID w1	.063 (.073)	.117 (.059)*	-.050 (.075)	.021 (.063)	.026 (.304)	.430 (.198)*
	immig2 w1	.368 (.080)***	.384 (.059)***	.302 (.076)***	.332 (.059)***	.053 (.190)	.070 (.142)
POC ID w3	ID w2	.820 (.070)***	.714 (.042)***	.801 (.079)***	.675 (.046)	-.855 (.595)	-.363 (.172)*
	immig2 w2	.034 (.064)	.028 (.042)	.008 (.068)	.017 (.043)	-.016 (.225)	.099 (.078)
immig2 w3	ID w2	.214 (.094)*	.117 (.059)*	.178 (.107)+	.021 (.063)	.983 (.453)*	.430 (.198)*
	immig2 w2	.404 (.086)***	.384 (.059)***	.382 (.093)***	.332 (.059)***	.164 (.177)	.070 (.142)
ID-attitude trait covariance						.011 (.006)+	.008 (.007)
W1 ID-attitude covariance		.014 (.007)*	.014 (.007)*	.014 (.007)*	.014 (.007)*	.004 (.005)	.007 (.005)
W2 ID-attitude covariance		-.001 (.005)	-.000 (.005)	.000 (.005)	.001 (.005)	-.003 (.011)	.006 (.008)
W3 ID-attitude covariance		.003 (.007)	.004 (.007)	.003 (.007)	.004 (.007)	.019 (.008)*	.013 (.006)*
CFI		.810	.806	.880	.874	1.000	1.000
RMSEA		.231	.165	.238	.172	.000	.000
SRMR		.063	.075	.033	.040	.014	.034
Chisq (df)		62.031 (4)***	67.000 (8)***	65.403 (4)***	72.210 (8)***	0.354 (1)	4.814 (5)
Chisq test			4.969 (4)		6.807 (4)		4.460 (4)

Note: N = 272 for all models.

Table A47

Study 2 American Identity & Immigration Attitudes (number of immigrants) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
Am. ID w2	ID w1	.746 (.025)***	.784 (.018)***	.751 (.026)***	.772 (.019)***	-.053 (.084)	-.093 (.095)
	immig1 w1	-.044 (.030)	-.023 (.022)	-.050 (.031)	-.009 (.022)	-.021 (.088)	.006 (.073)
immig1 w2	ID w1	.001 (.027)	-.009 (.020)	.016 (.029)	-.002 (.021)	.117 (.116)	.008 (.088)
	immig1 w1	.682 (.033)***	.686 (.024)***	.658 (.034)***	.659 (.024)***	-.108 (.137)	-.026 (.111)
Am. ID w3	ID w2	.831 (.027)***	.784 (.018)***	.798 (.027)***	.772 (.019)***	-.289 (.235)	-.093 (.095)
	immig1 w2	.002 (.031)	-.023 (.022)	.034 (.031)	-.009 (.022)	.052 (.137)	.006 (.073)
immig1 w3	ID w2	-.022 (.030)	-.009 (.020)	-.023 (.031)	-.002 (.021)	-.173 (.164)	.008 (.088)
	immig1 w2	.690 (.035)***	.686 (.024)***	.659 (.035)***	.659 (.024)***	.014 (.108)	-.026 (.111)
ID-attitude trait covariance						.001 (.003)	.001 (.003)
W1 ID-attitude covariance		.004 (.003)	.004 (.003)	.004 (.003)	.004 (.003)	.003 (.002)*	.002 (.001)$^{+}$
W2 ID-attitude covariance		.002 (.001)	.001 (.001)	.001 (.001)	.001 (.001)	.001 (.003)	.001 (.003)
W3 ID-attitude covariance		.000 (.001)	.000 (.001)	.001 (.001)	.001 (.001)	-.002 (.002)	-.000 (.001)
CFI		.897	.895	.924	.923	1.000	1.000
RMSEA		.266	.190	.254	.181	.000	.000
SRMR		.055	.058	.026	.027	.001	.014
Chisq (df)		190.770 (4)***	197.786 (8)***	173.710 (4)***	180.208 (8)***	0.021 (1)	3.987 (5)
Chisq test			7.016 (4)		6.498 (4)		3.966 (4)

Note: N = 658 for all models.

Table A48

Study 2 American Identity & Immigration Attitudes (number of immigrants) Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
Am. ID w2	ID w1	.736 (.045)***	.828 (.034)***	.692 (.048)***	.790 (.036)***	-.220 (.211)	-.265 (.164)
	immig 1 w1	-.080 (.047)$^{+}$	-.076 (.033)*	-.019 (.051)	-.046 (.036)	.230 (.236)	.143 (.088)
immig 1 w2	ID w1	-.003 (.062)	-.087 (.041)*	.077 (.065)	-.069 (.043)	.528 (.404)	.205 (.147)
	immig 1 w1	.673 (.065)***	.730 (.040)***	.555 (.069)***	.692 (.043)***	-.747 (.512)	-.299 (.129)*
Am. ID w3	ID w2	.923 (.049)***	.828 (.034)***	.870 (.051)***	.790 (.036)***	-1.019 (1.165)	-.265 (.164)
	immig 1 w2	-.050 (.046)	-.076 (.033)*	-.036 (.050)	-.046 (.036)	.056 (.373)	.143 (.088)
immig 1 w3	ID w2	-.124 (.054)*	-.087 (.041)*	-.139 (.054)**	-.069 (.043)	-.698 (.644)	.205 (.147)
	immig 1 w2	.764 (.051)***	.730 (.040)***	.764 (.053)***	.692 (.043)***	.093 (.191)	-.299 (.129)*
ID-attitude trait covariance						-.023 (.005)***	-.022 (.005)***
W1 ID-attitude cov		-.021 (.005)***	-.021 (.005)***	-.021 (.005)***	-.021 (.005)***	.002 (.004)	-.002 (.002)
W2 ID-attitude cov		-.008 (.003)**	-.009 (.003)**	-.007 (.002)**	-.008 (.003)**	.004 (.005)	.004 (.003)
W3 ID-attitude cov		.001 (.002)	.000 (.002)	.001 (.001)	.001 (.002)	-.003 (.003)	-.000 (.002)
CFI		.895	.884	.917	.902	1.000	.991
RMSEA		.257	.192	.275	.211	.000	.067
SRMR		.053	.087	.028	.044	.012	.043
Chisq (df)		75.836 (4)***	87.978 (8)***	86.406 (4)***	105.324 (8)***	0.867 (1)	11.122 (5)*
Chisq test			12.142 (4)*		18.918 (4)***		10.255 (4)*

Note: N = 272 for all models.

Table A49

Study 2 American Identity & Immigration Attitudes (ending criminal penalties) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
Am. ID w2	ID w1	.740 (.025)***	.782 (.019)***	.741 (.026)***	.770 (.019)***	-.061 (.081)	-.108 (.090)
	immig2 w1	-.065 (.025)*	-.025 (.018)	-.068 (.026)**	-.021 (.018)	-.055 (.033)$^{+}$	-.038 (.030)
immig2 w2	ID w1	-.065 (.043)	-.056 (.032)$^{+}$	-.065 (.045)	-.060 (.034)$^{+}$	-.063 (.190)	-.200 (.119)$^{+}$
	immig2 w1	.278 (.044)***	.287 (.031)***	.274 (.044)***	.288 (.032)***	-.047 (.084)	-.019 (.069)
Am. ID w3	ID w2	.832 (.027)***	.782 (.019)***	.801 (.027)***	.770 (.019)***	-.290 (.236)	-.108 (.090)
	immig2 w2	.014 (.025)	-.025 (.018)	.021 (.025)	-.021 (.018)	.035 (.074)	-.038 (.030)
immig2 w3	ID w2	-.049 (.049)	-.056 (.032)$^{+}$	-.057 (.050)	-.060 (.034)$^{+}$	-.090 (.212)	-.200 (.119)$^{+}$
	immig2 w2	.294 (.045)***	.287 (.031)***	.299 (.045)***	.288 (.032)***	.004 (.075)	-.019 (.069)
ID-attitude trait covariance						-.007 (.003)*	-.006 (.003)*
W1 ID-attitude cov		-.007 (.003)*	-.007 (.003)*	-.007 (.003)*	-.007 (.003)*	.000 (.002)	.001 (.002)
W2 ID-attitude cov		.000 (.002)	.001 (.002)	.000 (.002)	.000 (.002)	-.001 (.004)	-.004 (.003)
W3 ID-attitude cov		-.002 (.002)	-.002 (.002)	-.002 (.002)	-.002 (.002)	-.001 (.003)	-.003 (.002)
CFI		.899	.894	.929	.926	1.000	1.000
RMSEA		.218	.158	.209	.151	.000	.000
SRMR		.052	.056	.026	.027	.007	.018
Chisq (df)		128.758 (4)***	139.285 (8)***	119.093 (4)***	127.641 (8)***	0.347 (1)	4.271 (5)
Chisq test			10.527 (4)*		8.548 (4)$^{+}$		3.924 (4)

Note: N = 658 for all models.

Table A50

Study 2 American Identity & Immigration Attitudes (ending criminal penalties) Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
Am. ID w2	ID w1	.760 (.043)***	.839 (.033)***	.695 (.048)***	.779 (.036)***	-.128 (.207)	-.354 (.169)*
	immig2 w1	-.001 (.039)	-.025 (.027)	.007 (.039)	-.007 (.027)	.018 (.057)	-.015 (.049)
immig2 w2	ID w1	-.209 (.088)*	-.199 (.070)**	-.022 (.095)	-.053 (.078)	-.576 (.416)	-.118 (.306)
	immig2 w1	.339 (.080)***	.363 (.059)***	.300 (.077)***	.329 (.059)***	-.023 (.168)	.045 (.150)
Am. ID w3	ID w2	.932 (.047)***	.829 (.033)***	.874 (.051)***	.779 (.036)***	-.669 (.821)	-.354 (.169)
	immig2 w2	-.037 (.037)	-.025 (.027)	-.020 (.037)	-.007 (.027)	-.290 (.213)	-.015 (.049)
immig2 w3	ID w2	-.142 (.114)	-.199 (.070)**	-.095 (.130)	-.053 (.078)	-.866 (.878)	-.118 (.306)
	immig2 w2	.389 (.090)***	.363 (.059)***	.371 (.094)***	.329 (.059)***	-.037 (.228)	.045 (.150)
ID-attitude trait covariance						-.011 (.005)+	-.013 (.005)*
W1 ID-attitude cov		-.011 (.006)*	-.011 (.006)*	-.011 (.006)*	-.011 (.006)*	-.001 (.004)	-.003 (.003)
W2 ID-attitude cov		-.006 (.004)+	-.006 (.004)+	-.002 (.003)	-.002 (.003)	-.013 (.007)+	-.002 (.005)
W3 ID-attitude cov		-.000 (.004)	-.000 (.004)	.000 (.004)	-.000 (.004)	-.004 (.004)	-.001 (.003)
CFI		.925	.913	.946	.941	1.000	1.000
RMSEA		.172	.131	.181	.134	.000	.001
SRMR		.045	.064	.025	.029	.010	.039
Chisq (df)		36.365 (4)***	45.532 (8)***	39.561 (4)***	47.096 (8)***	0.206 (1)	5.003 (5)
Chisq test			9.167 (4)+		7.535 (4)		4.797 (4)

Note: N = 272 for all models

Table A51

Study 2 Racial Identity & Criminal Justice Attitudes (BLM/protests) Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
racial ID w2	ID w1	.712 (.031)***	.720 (.023)***	.712 (.031)***	.718 (.023)***	-.143 (.222)	.045 (.096)
	crim2 w1	.126 (.033)***	.145 (.024)***	.099 (.036)**	.134 (.026)***	-.504 (.495)	.258 (.095)**
crim2 w2	ID w1	.085 (.024)***	.060 (.018)**	.087 (.024)***	.057 (.018)**	-.028 (.187)	.086 (.058)
	crim2 w1	.844 (.025)***	.867 (.018)***	.814 (.028)***	.838 (.019)***	-.190 (.476)	.404 (.087)***
racial ID w3	ID w2	.729 (.035)***	.720 (.023)***	.726 (.035)***	.718 (.023)***	-.067 (.143)	.045 (.096)
	crim2 w2	.164 (.034)***	.145 (.024)***	.171 (.038)***	.134 (.026)***	.356 (.150)*	.258 (.095)**
crim2 w3	ID w2	.033 (.025)	.060 (.018)**	.025 (.025)	.057 (.018)**	-.047 (.092)	.086 (.058)
	crim2 w2	.891 (.025)***	.867 (.018)***	.863 (.027)***	.838 (.019)***	.410 (.101)***	.404 (.087)***
ID-attitude trait covariance						.032 (.003)***	.030 (.003)***
W1 ID-attitude cov		.030 (.003)***	.030 (.003)***	.030 (.003)***	.030 (.003)***	-.002 (.002)	-.000 (.001)
W2 ID-attitude cov		.004 (.001)***	.004 (.001)***	.004 (.001)***	.004 (.001)***	.001 (.004)	.006 (.002)***
W3 ID-attitude cov		.004 (.001)***	.004 (.001)***	.004 (.001)***	.004 (.001)***	.003 (.001)**	.003 (.001)***
CFI		.949	.949	.959	.958	1.000	.998
RMSEA		.229	.162	.223	.159	.000	.037
SRMR		.035	.038	.018	.020	.002	.022
Chisq (df)		142.442 (4)***	146.607 (8)***	134.309 (4)***	140.701 (8)***	0.113 (1)	9.390 (5)$^{+}$
Chisq test			4.165 (4)		6.392 (4)		9.277 (4)$^{+}$

Note: N = 658 for all models

Table A52

Study 2 Racial Identity & Criminal Justice Attitudes (BLM/protests) Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat[a]**
racial ID w2	ID w1	.797 (.046)***	.836 (.036)***	.791 (.047)***	.829 (.037)***	-.178 (.612)	-.062 (.259)
	crim2 w1	.041 (.039)	.029 (.030)	.002 (.056)	.040 (.042)	-.188 (.784)	-.077 (.219)
crim2 w2	ID w1	.043 (.036)	.047 (.024)+	.046 (.037)	.051 (.024)*	-.143 (.318)	-.043 (.098)
	crim2 w1	.891 (.030)***	.957 (.020)***	.888 (.043)***	.926 (.027)***	-.568 (.882)	-.735 (.193)***
racial ID w3	ID w2	.894 (.056)***	.836 (.036)***	.888 (.057)***	.829 (.037)***	.210 (.392)	-.062 (.259)
	crim2 w2	.013 (.044)	.029 (.030)	.097 (.064)	.040 (.042)	.666 (.878)	-.077 (.219)
crim2 w3	ID w2	.049 (.031)	.047 (.024)+	.057 (.031)+	.051 (.024)*	.300 (.860)	-.043 (.098)
	crim2 w2	1.000 (.025)***	.957 (.020)***	.953 (.035)***	.926 (.027)***	-1.165 (1.808)	-.735 (.193)***
ID-attitude trait covariance						.020 (.006)**	.019 (.006)**
W1 ID-attitude cov		.017 (.006)**	.017 (.006)**	.017 (.006)**	.017 (.006)**	-.003 (.003)	-.000 (.001)
W2 ID-attitude cov		.000 (.002)	-.000 (.002)	.000 (.002)	.000 (.002)	-.001 (.007)	-.002 (.002)
W3 ID-attitude cov		.000 (.001)	.000 (.001)	.001 (.001)	.001 (.001)	.002 (.003)	.003 (.003)
CFI		.938	.932	.958	.958	1.000	1.000
RMSEA		.238	.176	.224	.159	.000	.000
SRMR		.024	.047	.012	.018	.001	.017
Chisq (df)		65.556 (4)***	75.511 (8)***	58.473 (4)***	63.284 (8)***	0.009 (1)	2.270 (5)
Chisq test			9.955 (4)*		4.811 (4)		2.261 (4)

Note: N = 272 for all models.

[a] Warning: some estimated lv variances are negative (fcrimcompw2).

Table A53

Study 2 Racial Identity & Criminal Justice Attitudes (mandatory minimum sentence, continuous) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
racial ID w2	ID w1	.769 (.028)***	.789 (.021)***	.746 (.029)***	.768 (.022)***	-.160 (.159)	-.052 (.125)
	crim1 w1	.005 (.017)	.018 (.012)	.009 (.017)	.019 (.012)	-.092 (.036)**	-.079 (.026)**
crim1 w2	ID w1	.170 (.066)**	.103 (.048)*	.136 (.068)*	.070 (.050)	-.119 (.355)	-.469 (.185)*
	crim1 w1	.366 (.039)***	.427 (.028)***	.350 (.040)***	.409 (.029)***	-.101 (.096)	-.068 (.075)
racial ID w3	ID w2	.809 (.031)***	.789 (.021)***	.791 (.032)***	.768 (.022)***	-.000 (.146)	-.052 (.125)
	crim1 w2	.034 (.018)$^{+}$	.018 (.012)	.031 (.018)$^{+}$	.019 (.012)	-.021 (.048)	-.079 (.026)**
crim1 w3	ID w2	.030 (.068)	.103 (.048)*	-.004 (.071)	.070 (.050)	-.459 (.235)$^{+}$	-.469 (.185)*
	crim1 w2	.497 (.040)***	.427 (.028)***	.474 (.041)***	.409 (.029)***	.083 (.084)	-.068 (.075)
ID-attitude trait covariance						.018 (.004)***	.019 (.004)***
W1 ID-attitude cov		.011 (.005)*	.011 (.005)*	.011 (.005)*	.011 (.005)*	-.007 (.004)*	-.007 (.003)*
W2 ID-attitude cov		-.001 (.003)	-.001 (.003)	-.000 (.003)	-.000 (.003)	-.007 (.006)	-.012 (.005)**
W3 ID-attitude cov		.004 (.003)	.004 (.003)	.004 (.003)	.004 (.003)	-.001 (.003)	-.001 (.003)
CFI		.888	.884	.919	.916	1.000	.998
RMSEA		.231	.167	.227	.163	.000	.024
SRMR		.064	.068	.031	.033	.005	.024
Chisq (df)		144.466 (4)***	154.033 (8)***	139.064 (4)***	147.458 (8)***	0.247 (1)	6.966 (5)
Chisq test			9.567 (4)*		8.394 (4)$^{+}$		6.719 (4)

Note: N = 658 for all models.

Table A54

Study 2 Racial Identity & Criminal Justice Attitudes (mandatory minimum sentence, categorical) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat[a, b]
racial ID w2	ID w1	.782 (.031)***	.834 (.024)***	.761 (.030)***	.820 (.022)***
	crim1 w1	.002 (.011)	.014 (.007)*	.007 (.012)	.016 (.007)*
crim1 w2	ID w1	.286 (.216)	.365 (.146)*	.249 (.225)	.275 (.158)$^{+}$
	crim1 w1	.654 (.059)***	.612 (.023)***	.684 (.071)***	.587 (.028)***
racial ID w3	ID w2	.876 (.042)***	.834 (.024)***	.872 (.041)***	.820 (.022)***
	crim1 w2	.021 (.008)**	.014 (.007)*	.020 (.008)*	.016 (.007)*
crim1 w3	ID w2	.411 (.228)$^{+}$	.365 (.146)*	.266 (.246)	.275 (.158)$^{+}$
	crim1 w2	.581 (.037)***	.612 (.023)***	.526 (.039)***	.587 (.028)***
ID-attitude trait covariance					
W1 ID-attitude covariance		.034 (.014)*	.027 (.013)*	.033 (.014)*	.030 (.013)*
W2 ID-attitude covariance		-.014 (.011)	-.019 (.013)	-.013 (.011)	-.014 (.012)
W3 ID-attitude covariance		-.010 (.009)	-.003 (.010)	-.006 (.009)	-.005 (.009)
CFI		.967/.865	.968/ .893	.983/.924	.984/ .935
RMSEA		.109/.174	.075/ .109	.095/.165	.066/ .108
SRMR		.157	.157	.072	.068
Chisq (df)		35.374 (4)***/ 83.432 (4)***	37.799 (8)***/ 70.875 (8)***	27.492 (4)***/ 75.645 (4)***	31.186 (8)***/ 69.752 (8)***
Chisq test			2.425 (4)		3.694 (4)

Note: N = 658 for all models.

Note: Reported CFI, RMSEA, and χ^2 values are non-robust/robust.

[a] Warning: trouble constructing W matrix.
[b] Warning: variance-covariance matrix of estimated parameters doesn't appear to be positive definite. Smallest eigenvalue close to 0.

Table A55

Study 2 Racial Identity & Criminal Justice Attitudes (mandatory minimum sentence, continuous) Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
racial ID w2	ID w1	.805 (.045)***	.843 (.035)***	.789 (.046)***	.830 (.037)***	.068 (.390)	.317 (.242)
	crim1 w1	-.020 (.029)	-.006 (.023)	-.052 (.032)	-.026 (.024)	.025 (.100)	-.042 (.047)
crim1 w2	ID w1	-.239 (.112)*	-.201 (.083)*	-.245 (.116)*	-.237 (.085)**	-.716 (.599)	-.810 (.297)**
	crim1 w1	.464 (.072)***	.506 (.053)***	.439 (.079)***	.481 (.056)***	.093 (.183)	.137 (.145)
racial ID w3	ID w2	.904 (.056)***	.843 (.035)***	.905 (.059)***	.830 (.037)***	.303 (.288)	.317 (.242)
	crim1 w2	.022 (.036)	-.006 (.023)	.017 (.037)	-.026 (.024)	-.053 (.097)	-.042 (.047)
crim1 w3	ID w2	-.147 (.122)	-.201 (.083)*	-.227 (.124)$^{+}$	-.237 (.085)**	-.842 (.574)	-.810 (.297)**
	crim1 w2	.558 (.078)***	.506 (.053)***	.516 (.078)***	.481 (.056)***	.102 (.214)	.137 (.145)
ID-attitude trait covariance						-.005 (.011)	.000 (.010)
W1 ID-attitude cov		.006 (.009)	.006 (.009)	.006 (.009)	.006 (.009)	.010 (.011)	.004 (.009)
W2 ID-attitude cov		-.002 (.005)	-.002 (.005)	-.002 (.005)	-.002 (.005)	-.013 (.010)	-.014 (.008)$^{+}$
W3 ID-attitude cov		-.005 (.005)	-.005 (.006)	-.006 (.005)	-.005 (.005)	-.010 (.007)	-.011 (.005)$^{+}$
CFI		.964	.966	.977	.976	1.000	1.000
RMSEA		.115	.080	.113	.081	.000	.000
SRMR		.040	.051	.019	.024	.013	.023
Chisq (df)		18.288 (4)**	21.848 (8)**	17.884 (4)**	22.207 (8)**	0.464 (1)	1.910 (5)
Chisq test			3.560 (4)		4.323 (4)		1.446 (4)

Note: N = 272 for all models.

Table A56

Study 2 Racial Identity & Criminal Justice Attitudes (mandatory minimum sentence, categorical) Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat[a]**
racial ID w2	ID w1	.799 (.071)***	.854 (.051)***	.797 (.070)***	.850 (.051)***
	crim1 w1	-.032 (.028)	-.016 (.017)	-.063 (.032)$^+$	-.029 (.018)
crim1 w2	ID w1	-.675 (.405)$^+$	-.472 (.261)$^+$	-.754 (.428)$^+$	-.593 (.281)*
	crim1 w1	.714 (.089)***	.613 (.038)***	.784 (.113)***	.591 (.045)***
racial ID w3	ID w2	.926 (.087)***	.854 (.051)***	.935 (.087)***	.850 (.051)***
	crim1 w2	.000 (.021)	-.016 (.017)	-.002 (.020)	-.029 (.018)
crim1 w3	ID w2	-.461 (.449)	-.472 (.261)$^+$	-.773 (.470)	-.593 (.281)*
	crim1 w2	.529 (.063)***	.613 (.038)***	.459 (.068)***	.591 (.045)***
ID-attitude trait covariance					
W1 ID-attitude covariance		.013 (.024)	.005 (.024)	.014 (.024)	.002 (.024)
W2 ID-attitude covariance		-.005 (.029)	-.015 (.032)	.007 (.029)	-.007 (.029)
W3 ID-attitude covariance		-.016 (.020)	-.005 (.026)	-.020 (.019)	-.012 (.023)
CFI		.996/.946	1.000/ .970	.999/.951	1.000/ .963
RMSEA		.037/.105	.000/ .056	.016/.119	.005/ .073
SRMR		.155	.153	.079	.067
Chisq (df)		5.450 (4)/ 16.035 (4)**	7.766 (8)/ 14.743 (8)$^+$	4.295 (4)/ 19.302 (4)**	8.050 (8)/ 19.519 (8)*
Chisq test			2.316 (4)		3.755 (4)

Note: N = 272 for all models.

Note: Reported CFI, RMSEA, and χ^2 values are non-robust/robust.

[a] Warning: trouble constructing W matrix.

Table A57

Study 2 POC Identity & Criminal Justice Attitudes (BLM/protests) Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
POC ID w2	ID w1	.706 (.031)***	.735 (.023)***	.700 (.031)***	.728 (.023)***	.084 (.183)	.132 (.100)
	crim2 w1	.175 (.033)***	.136 (.024)***	.142 (.037)***	.122 (.027)***	.103 (.413)	.260 (.106)*
crim2 w2	ID w1	.078 (.023)**	.064 (.017)***	.083 (.023)***	.062 (.017)***	-.039 (.166)	.115 (.056)*
	crim2 w1	.849 (.025)***	.865 (.018)***	.818 (.027)***	.837 (.019)***	-.198 (.469)	.396 (.091)***
POC ID w3	ID w2	.774 (.034)***	.735 (.023)***	.767 (.035)***	.728 (.023)***	.217 (.118)$^{+}$	.132 (.100)
	crim2 w2	.089 (.035)*	.136 (.024)***	.094 (.039)*	.122 (.027)***	.131 (.137)	.260 (.106)*
crim2 w3	ID w2	.049 (.024)*	.064 (.017)***	.038 (.024)	.062 (.017)***	.083 (.083)	.115 (.056)*
	crim2 w2	.882 (.024)***	.865 (.018)***	.857 (.027)***	.837 (.019)***	.362 (.104)***	.396 (.091)***
ID-attitude trait covariance						.031 (.003)***	.030 (.003)***
W1 ID-attitude cov		.029 (.003)***	.029 (.003)***	.029 (.003)***	.029 (.003)***	-.002 (.002)	-.001 (.002)
W2 ID-attitude cov		.004 (.001)***	.004 (.001)***	.004 (.001)***	.004 (.001)***	.004 (.003)	.006 (.002)***
W3 ID-attitude cov		.002 (.001)*	.002 (.001)*	.002 (.001)*	.002 (.001)*	.002 (.001)	.002 (.001)$^{+}$
CFI		.958	.958	.966	.966	1.000	1.000
RMSEA		.205	.146	.201	.143	.000	.010
SRMR		.030	.031	.015	.016	.001	.015
Chisq (df)		114.341 (4)***	119.808 (8)***	110.400 (4)***	115.391 (8)***	0.007 (1)	5.345 (5)
Chisq test			5.467 (4)		4.991 (4)		5.338 (4)

Note: N = 658 for all models.

Table A58

Study 2 POC Identity & Criminal Justice Attitudes (BLM/protests) Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat[a]
POC ID w2	ID w1	.608 (.057)***	.674 (.047)***	.589 (.057)***	.657 (.048)***	-.358 (.213)$^{+}$	-.462 (.158)**
	crim2 w1	.116 (.057)*	.098 (.045)*	.126 (.073)$^{+}$	.093 (.059)	.121 (.423)	-.242 (.258)
crim2 w2	ID w1	-.009 (.034)	.037 (.024)	-.011 (.034)	.038 (.024)	-.018 (.174)	-.068 (.057)
	crim2 w1	.902 (.034)***	.949 (.022)***	.901 (.045)***	.922 (.028)***	-.155 (.339)	-.702 (.202)**
POC ID w3	ID w2	.793 (.080)***	.674 (.047)***	.788 (.082)***	.657 (.048)***	-.706 (.842)	-.462 (.158)**
	crim2 w2	.054 (.069)	.098 (.045)*	.034 (.095)	.093 (.059)	-1.247 (4.939)	-.242 (.258)
crim2 w3	ID w2	.081 (.031)**	.037 (.024)	.080 (.031)**	.038 (.024)	-.146 (1.830)	-.068 (.057)
	crim2 w2	.974 (.027)***	.949 (.022)***	.934 (.036)***	.922 (.028)***	-3.804 (9.286)	-.702 (.202)**
ID-attitude trait covariance						.046 (.008)***	.049 (.007)***
W1 ID-attitude cov		.052 (.008)***	.052 (.008)***	.052 (.008)***	.052 (.008)***	.005 (.007)	.002 (.001)
W2 ID-attitude cov		.004 (.002)$^{+}$	.005 (.002)*	.004 (.002)*	.004 (.002)*	-.002 (.004)	-.006 (.003)*
W3 ID-attitude cov		.002 (.002)	.003 (.002)	.003 (.002)	.003 (.002)	.013 (.013)	.009 (.004)*
CFI		.903	.892	.931	.928	.998	1.000
RMSEA		.295	.221	.286	.207	.093	.000
SRMR		.050	.073	.026	.032	.027	.036
Chisq (df)		98.933 (4)***	113.801 (8)***	92.768 (4)***	101.054 (8)***	3.371 (1)$^{+}$	4.688 (5)
Chisq test			14.868 (4)**		8.286 (4)$^{+}$		1.317 (4)

Note: N = 272 for all models.

[a] Warning: some estimated lv variances are negative (fcrimcompw2).

Table A59

Study 2 POC Identity & Criminal Justice Attitudes (mandatory minimum sentence, continuous) Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
POC ID w2	ID w1	.778 (.028)***	.796 (.021)***	.743 (.029)***	.770 (.022)***	.086 (.167)	.234 (.132)$^{+}$
	crim1 w1	.015 (.017)	.012 (.013)	.016 (.018)	.013 (.013)	-.016 (.038)	-.015 (.031)
crim1 w2	ID w1	.092 (.065)	.052 (.046)	.053 (.067)	.012 (.048)	-.141 (.290)	-.175 (.202)
	crim1 w1	.368 (.040)***	.431 (.028)***	.351 (.040)***	.412 (.029)***	-.135 (.088)	-.062 (.080)
POC ID w3	ID w2	.815 (.030)***	.796 (.021)***	.802 (.032)***	.770 (.022)***	.265 (.109)*	.234 (.132)$^{+}$
	crim1 w2	.009 (.018)	.012 (.013)	.008 (.019)	.013 (.013)	-.013 (.041)	-.015 (.031)
crim1 w3	ID w2	.005 (.065)	.052 (.046)	-.037 (.068)	.012 (.048)	-.198 (.196)	-.175 (.202)
	crim1 w2	.499 (.040)***	.431 (.028)***	476 (.041)***	.412 (.029)***	.073 (.082)	-.062 (.080)
ID-attitude trait covariance						.014 (.005)**	.014 (.005)**
W1 ID-attitude cov		.012 (.005)*	.012 (.005)*	.012 (.005)*	.012 (.005)*	-.002 (.004)	-.002 (.003)
W2 ID-attitude cov		.004 (.003)	.004 (.003)	.003 (.003)	.003 (.003)	.000 (.005)	-.001 (.006)
W3 ID-attitude cov		.003 (.003)	.003 (.003)	.003 (.003)	.003 (.003)	-.000 (.003)	-.001 (.003)
CFI		.918	.916	.940	.938	1.000	.998
RMSEA		.196	.140	.194	.140	.000	.030
SRMR		.059	.063	.028	.030	.003	.024
Chisq (df)		105.009 (4)***	111.882 (8)***	102.972 (4)***	110.554 (8)***	0.086 (1)	7.966 (5)
Chisq test			6.873 (4)		7.582 (4)		7.880 (4)$^{+}$

Note: N = 658 for all models.

Table A60

Study 2 POC Identity & Criminal Justice Attitudes (mandatory minimum sentence, categorical) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat[a, b]
POC ID w2	ID w1	.793 (.033)***	.833 (.024)***	.757 (.030)***	.819 (.023)***
	crim1 w1	.001 (.012)	.005 (.007)	.003 (.013)	.008 (.008)
crim1 w2	ID w1	.104 (.219)	.184 (.141)	.053 (.226)	.084 (.151)
	crim1 w1	.659 (.060)***	.618 (.023)***	.687 (.071)***	.592 (.028)***
POC ID w3	ID w2	.867 (.043)***	.833 (.024)***	.874 (.043)***	.819 (.023)***
	crim1 w2	.008 (.009)	.005 (.007)	.009 (.009)	.008 (.008)
crim1 w3	ID w2	.253 (.216)	.184 (.141)	.082 (.232)	.084 (.151)
	crim1 w2	.584 (.037)***	.618 (.023)***	.530 (.039)***	.592 (.028)***
ID-attitude trait covariance					
W1 ID-attitude covariance		.036 (.014)*	.033 (.013)*	.035 (.014)*	.034 (.014)*
W2 ID-attitude covariance		.006 (.012)	.003 (.013)	.005 (.012)	.005 (.012)
W3 ID-attitude covariance		-.006 (.009)	-.001 (.011)	-.000 (.009)	-.000 (.010)
CFI		.967/.865	.970/ .899	.984/.925	.984/ .937
RMSEA		.108/.173	.073/ .106	.093/.163	.064/ .106
SRMR		.159	.158	.073	.069
Chisq (df)		34.432 (4)***/ 82.713 (4)***	35.832 (8)***/ 66.554 (8)***	26.513 (4)***/ 74.069 (4)***	29.865 (8)***/ 67.175 (8)***
Chisq test			1.400 (4)		3.352 (4)

Note: N = 658 for all models.

Note: Reported CFI, RMSEA, and χ^2 values are non-robust/robust.

[a] Warning: trouble constructing W matrix.
[b] Warning: variance-covariance matrix of estimated parameters doesn't appear to be positive definite. Smallest eigenvalue close to 0.

Table A61

Study 2 POC Identity & Criminal Justice Attitudes (mandatory minimum sentence, continuous) Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
POC ID w2	ID w1	.665 (.050)***	.716 (.042)***	.616 (.055)***	.670 (.046)***	-.208 (.171)	-.408 (.160)*
	crim1 w1	.024 (.038)	-.003 (.031)	-.019 (.042)	-.028 (.033)	.032 (.062)	.053 (.064)
crim1 w2	ID w1	-.102 (.096)	-.029 (.073)	-.057 (.107)	-.009 (.080)	-.355 (.389)	.392 (.259)
	crim1 w1	.463 (.073)***	.518 (.054)***	.441 (.081)***	.502 (.056)***	.110 (.190)	.174 (.179)
POC ID w3	ID w2	.817 (.070)***	.716 (.042)***	.791 (.080)***	.670 (.046)***	-.847 (.604)	-.408 (.160)*
	crim1 w2	-.043 (.050)	-.003 (.031)	-.039 (.051)	-.028 (.033)	-.291 (.214)	.053 (.064)
crim1 w3	ID w2	.071 (.109)	-.029 (.073)	.043 (.120)	-.009 (.080)	.630 (.478)	.392 (.259)
	crim1 w2	.582 (.077)***	.518 (.054)***	.556 (.077)***	.502 (.056)***	.372 (.192)$^{+}$	.174 (.179)
ID-attitude trait covariance						.004 (.010)	-.004 (.010)
W1 ID-attitude covariance		.008 (.010)	.008 (.010)	.008 (.010)	.008 (.010)	.002 (.009)	.006 (.008)
W2 ID-attitude covariance		-.009 (.007)	-.009 (.007)	-.010 (.007)	-.010 (.007)	-.018 (.013)	.007 (.011)
W3 ID-attitude covariance		-.007 (.008)	-.007 (.008)	-.009 (.007)	-.009 (.008)	.002 (.008)	.001 (.007)
CFI		.853	.844	.914	.912	1.000	.995
RMSEA		.211	.154	.211	.151	.000	.036
SRMR		.059	.075	.030	.037	.014	.046
Chisq (df)		52.532 (4)***	59.731 (8)***	52.377 (4)***	57.402 (8)***	0.550 (1)	6.784 (5)
Chisq test			7.199 (4)		5.025 (4)		6.234 (4)

Note: N = 272 for all models.

Table A62

Study 2 POC Identity & Criminal Justice Attitudes (mandatory minimum sentence, categorical) Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat[a]
POC ID w2	ID w1	.717 (.070)***	.847 (.068)***	.654 (.064)***	.805 (.060)***
	crim1 w1	-.009 (.029)	-.015 (.019)	-.054 (.034)	-.035 (.021)$^{+}$
crim1 w2	ID w1	-.514 (.282)$^{+}$	-.215 (.206)	-.307 (.298)	-.305 (.219)
	crim1 w1	.714 (.092)***	.624 (.036)***	.774 (.114)***	.605 (.044)***
POC ID w3	ID w2	.978 (.128)***	.847 (.068)***	1.016 (.134)***	.805 (.060)***
	crim1 w2	-.011 (.025)	-.015 (.019)	-.011 (.025)	-.035 (.021)$^{+}$
crim1 w3	ID w2	.112 (.359)	-.215 (.206)	-.340 (.386)	-.305 (.219)
	crim1 w2	.555 (.064)***	.624 (.036)***	.494 (.072)***	.605 (.044)***
ID-attitude trait covariance					
W1 ID-attitude covariance		.019 (.026)	.013 (.025)	.020 (.026)	.015 (.026)
W2 ID-attitude covariance		-.001 (.027)	-.007 (.029)	.012 (.028)	.011 (.028)
W3 ID-attitude covariance		-.013 (.023)	.011 (.028)	-.010 (.023)	-.002 (.025)
CFI		.993/.930	.994/ .941	.998/.949	1.000/ .956
RMSEA		.043/.105	.028/ .068	.027/.118	.008/ .078
SRMR		.162	.165	.081	.071
Chisq (df)		5.988 (4)/ 15.928 (4)**	9.757 (8)/ 18.122 (8)*	4.778 (4)/ 19.047 (4)**	8.135 (8)/ 21.222 (8)**
Chisq test			3.769 (4)		3.357 (4)

Note: N = 272 for all models.

Note: Reported CFI, RMSEA, and χ^2 values are non-robust/robust.

[a] Warning: trouble constructing W matrix.

Table A63

Study 2 American Identity & Criminal Justice Attitudes (BLM/protests) Panel Model Results, Black Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat
Am. ID w2	ID w1	.744 (.025)***	.784 (.018)***	.747 (.026)***	.772 (.019)***	-.082 (.087)	-.083 (.094)
	crim2 w1	.003 (.030)	.007 (.021)	.006 (.035)	.018 (.024)	-.326 (.277)	-.039 (.119)
crim2 w2	ID w1	-.007 (.019)	-.010 (.013)	.005 (.020)	-.011 (.014)	-.102 (.107)	-.085 (.065)
	crim2 w1	.887 (.023)***	.898 (.000)***	.854 (.026)***	.866 (.018)***	-.188 (.443)	.468 (.079)***
Am. ID w3	ID w2	.830 (.027)***	.784 (.018)***	.799 (.027)***	.772 (.019)***	-.322 (.249)	-.083 (.094)
	crim2 w2	.011 (.030)	.007 (.021)	.028 (.034)	.018 (.024)	.045 (.202)	-.039 (.119)
crim2 w3	ID w2	-.013 (.019)	-.010 (.013)	-.027 (.020)	-.011 (.014)	-.138 (.111)	-.085 (.065)
	crim2 w2	.908 (.021)***	.898 (.015)***	.877 (.024)***	.866 (.018)***	.407 (.099)***	.468 (.079)***
ID-attitude trait covariance						.004 (.003)	.003 (.003)
W1 ID-attitude cov		.002 (.003)	.002 (.003)	.002 (.003)	.002 (.003)	-.001 (.002)	-.001 (.001)
W2 ID-attitude cov		.003 (.001)**	.003 (.001)**	.003 (.001)**	.003 (.001)**	-.000 (.002)	.001 (.002)
W3 ID-attitude cov		.002 (.001)**	.002 (.001)**	.002 (.001)**	.002 (.001)**	.001 (.001)	.001 (.001)
CFI		.937	.936	.954	.954	1.000	.999
RMSEA		.251	.179	.237	.168	.000	.033
SRMR		.036	.040	.017	.018	.002	.019
Chisq (df)		169.780 (4)***	176.056 (8)***	151.926 (4)***	156.129 (8)***	0.099 (1)	8.476 (5)
Chisq test			6.276 (4)		4.203 (4)		8.377 (4)$^{+}$

Note: N = 658 for all models.

Table A64

Study 2 American Identity & Criminal Justice Attitudes (BLM/protests) Panel Model Results, Latino Participants

		CLPM	CLPM stat	CLPM w/ cont	CLPM w/ cont stat	RI-CLPM	RI-CLPM stat[a]
Am. ID w2	ID w1	.719 (.043)***	.810 (.035)***	.686 (.047)***	.773 (.037)***	-.204 (.175)	-.272 (.165)+
	crim2 w1	-.120 (.036)**	-.082 (.027)**	-.111 (.048)*	-.062 (.036)+	-.171 (.317)	.054 (.190)
crim2 w2	ID w1	-.096 (.036)**	-.023 (.027)	-.095 (.041)*	-.011 (.029)	.043 (.244)	.082 (.113)
	crim2 w1	.875 (.031)***	.957 (.022)***	.890 (.042)***	.933 (.028)***	-.393 (.682)	-.802 (.202)***
Am. ID w3	ID w2	.918 (.050)***	.810 (.035)***	.878 (.052)***	.773 (.037)***	-.620 (1.393)	-.272 (.165)+
	crim2 w2	-.044 (.037)	-.082 (.027)**	.003 (.051)	-.062 (.036)+	.973 (1.975)	.054 (.190)
crim2 w3	ID w2	.045 (.036)	-.023 (.027)	.060 (.037)	-.011 (.029)	-.210 (1.835)	.082 (.113)
	crim2 w2	1.022 (.027)***	.957 (.022)***	.973 (.036)***	.933 (.028)***	-1.602 (2.867)	-.802 (.202)***
ID-attitude trait covariance						-.033 (.006)***	-.034 (.006)***
W1 ID-attitude cov		-.029 (.006)***	-.029 (.006)***	-.029 (.006)***	-.029 (.006)***	.003 (.003)	.003 (.001)**
W2 ID-attitude cov		.002 (.001)	.003 (.002)+	.002 (.001)+	.003 (.001)*	-.001 (.002)	-.000 (.002)
W3 ID-attitude cov		-.000 (.001)	.000 (.001)	.001 (.001)	.001 (.001)	-.001 (.007)	.001 (.003)
CFI		.923	.905	.945	.937	.999	1.000
RMSEA		.276	.217	.270	.205	.047	.000
SRMR		.027	.056	.015	.023	.013	.016
Chisq (df)		87.068 (4)***	110.606 (8)***	83.205 (4)***	99.086 (8)***	1.606 (1)	2.555 (5)
Chisq test			23.538 (4)***		15.881 (4)**		0.949 (4)

Note: N = 272 for all models.

[a] Warning: some estimated lv variances are negative (fcrimcompw2).

Table A65

Study 2 American Identity & Criminal Justice Attitudes (mandatory minimum sentence, continuous) Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
American ID w2	ID w1	.743 (.025)***	.783 (.018)***	.744 (.026)***	.770 (.019)***	-.056 (.084)	-.069 (.097)
	crim1 w1	-.043 (.017)*	-.016 (.013)	-.038 (.017)*	-.016 (.013)	-.004 (.027)	-.014 (.027)
crim1 w2	ID w1	-.052 (.057)	-.085 (.042)*	-.106 (.060)$^{+}$	-.119 (.043)**	.216 (.241)	-.087 (.181)
	crim1 w1	.371 (.039)***	.429 (.028)***	.348 (.040)***	.404 (.029)***	-.143 (.090)	-.026 (.085)
American ID w3	ID w2	.834 (.027)***	.783 (.018)***	.802 (.028)***	.770 (.019)***	-.291 (.240)	-.069 (.097)
	crim1 w2	.019 (.018)	-.016 (.013)	.010 (.018)	-.016 (.013)	.010 (.062)	-.014 (.027)
crim1 w3	ID w2	-.104 (.060)$^{+}$	-.085 (.042)*	-.123 (.062)*	-.119 (.043)**	-.307 (.283)	-.087 (.181)
	crim1 w2	.492 (.040)***	.429 (.028)***	.464 (.041)***	.404 (.029)***	.066 (.081)	-.026 (.085)
ID-attitude trait covariance						-.009 (.004)*	-.008 (.004)$^{+}$
W1 ID-attitude covariance		-.002 (.005)	-.002 (.005)	-.002 (.005)	-.002 (.005)	.007 (.003)*	.005 (.003)$^{+}$
W2 ID-attitude covariance		-.005 (.003)	-.005 (.003)	-.004 (.003)	-.004 (.003)	-.003 (.005)	-.006 (.005)
W3 ID-attitude covariance		.001 (.003)	.001 (.003)	.000 (.003)	.000 (.003)	-.000 (.003)	.002 (.002)
CFI		.894	.885	.926	.923	1.000	.997
RMSEA		.237	.175	.225	.163	.000	.036
SRMR		.059	.067	.028	.031	.001	.025
Chisq (df)		151.595 (4)***	168.325 (8)***	137.654 (4)***	147.598 (8)***	0.017 (1)	9.312 (5)$^{+}$
Chisq test			16.730 (4)**		9.944 (4)*		9.295 (4)$^{+}$

Note: N = 658 for all models.

Table A66

Study 2 American Identity & Criminal Justice Attitudes (mandatory minimum sentence, categorical) Panel Model Results, Black Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat[a, b]**
American ID w2	ID w1	.769 (.035)***	.860 (.024)***	.761 (.034)***	.839 (.023)***
	crim1 w1	-.039 (.013)**	-.012 (.007)$^{+}$	-.041 (.015)**	-.014 (.008)$^{+}$
crim1 w2	ID w1	-.084 (.180)	-.216 (.127)$^{+}$	-.144 (.200)	-.326 (.143)*
	crim1 w1	.660 (.058)***	.619 (.023)***	.672 (.070)***	.579 (.030)***
American ID w3	ID w2	.942 (.044)***	.860 (.024)***	.903 (.041)***	.839 (.023)***
	crim1 w2	.005 (.009)	-.012 (.007)$^{+}$	.001 (.009)	-.014 (.008)$^{+}$
crim1 w3	ID w2	-.486 (.219)*	-.216 (.127)$^{+}$	-.635 (.231)**	-.326 (.143)*
	crim1 w2	.578 (.037)***	.619 (.023)***	.509 (.040)***	.579 (.030)***
ID-attitude trait covariance					
W1 ID-attitude covariance		-.006 (.016)	-.014 (.015)	-.006 (.016)	-.012 (.015)
W2 ID-attitude covariance		.004 (.012)	.003 (.014)	.007 (.012)	.006 (.013)
W3 ID-attitude covariance		.015 (.009)	.008 (.012)	.017 (.010)$^{+}$	.011 (.011)
CFI		.967/.860	.964/ .887	.984/.928	.983/ .937
RMSEA		.106/.173	.078/ .110	.089/.156	.065/ .104
SRMR		.160	.162	.070	.066
Chisq (df)		33.304 (4)***/ 82.805 (4)***	39.898 (8)***/ 71.219 (8)***	24.641 (4)***/ 68.216 (4)***	30.394 (8)***/ 64.463 (8)***
Chisq test			6.594 (4)		5.753 (4)

Note: N = 658 for all models.

Note: Reported CFI, RMSEA, and χ^2 values are non-robust/robust.

[a] Warning: trouble constructing W matrix

[b] Warning: variance-covariance matrix of estimated parameters doesn't appear to be positive definite. Smallest eigenvalue close to 0.

Table A67

Study 2 American Identity & Criminal Justice Attitudes (mandatory minimum sentence, continuous) Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat**	**RI-CLPM**	**RI-CLPM stat**
American ID w2	ID w1	.754 (.043)***	.845 (.033)***	.690 (.048)***	.779 (.037)***	-.222 (.204)	-.394 (.161)*
	crim2 w1	-.031 (.027)	.001 (.020)	-.025 (.029)	-.005 (.020)	.010 (.040)	.017 (.042)
crim2 w2	ID w1	-.064 (.116)	-.097 (.087)	-.226 (.133)$^+$	-.175 (.099)$^+$	.495 (.661)	-.098 (.412)
	crim2 w1	.460 (.074)***	.514 (.054)***	.440 (.080)***	.493 (.056)***	.101 (.187)	.191 (.172)
American ID w3	ID w2	.950 (.046)***	.845 (.033)***	.883 (.052)***	.779 (.037)***	-.676 (.832)	-.394 (.161)*
	crim2 w2	.032 (.028)	.001 (.020)	.017 (.028)	-.005 (.020)	.197 (.154)	.017 (.042)
crim2 w3	ID w2	-.163 (.126)	-.097 (.087)	-.138 (.145)	-.175 (.099)$^+$	.675 (.980)	-.098 (.412)
	crim2 w2	.564 (.077)***	.514 (.054)***	.537 (.077)***	.493 (.056)***	.218 (.189)	.191 (.172)
ID-attitude trait covariance						-.022 (.009)**	-.020 (.008)*
W1 ID-attitude covariance		-.019 (.008)*	-.019 (.008)*	-.019 (.008)*	-.019 (.008)*	.003 (.006)	.005 (.005)
W2 ID-attitude covariance		-.002 (.005)	-.002 (.005)	-.004 (.005)	-.004 (.005)	.008 (.011)	-.007 (.008)
W3 ID-attitude covariance		-.006 (.004)	-.006 (.005)	-.008 (.004)*	-.008 (.004)$^+$	.002 (.005)	-.001 (.004)
CFI		.923	.905	.950	.942	1.000	1.000
RMSEA		.183	.144	.185	.140	.000	.000
SRMR		.041	.064	.022	.027	.001	.033
Chisq (df)		40.356 (4)***	52.891 (8)***	41.072 (4)***	50.384 (8)***	0.003 (1)	4.547 (5)
Chisq test			12.535 (4)*		9.312 (4)$^+$		4.544 (4)

Note: N = 272 for all models.

Table A68

Study 2 American Identity & Criminal Justice Attitudes (mandatory minimum sentence, categorical) Panel Model Results, Latino Participants

		CLPM	**CLPM stat**	**CLPM w/ cont**	**CLPM w/ cont stat[a]**
American ID w2	ID w1	.760 (.069)***	.921 (.054)***	.713 (.058)***	.868 (.047)***
	crim1 w1	-.038 (.024)	-.018 (.015)	-.026 (.026)	-.007 (.015)
crim1 w2	ID w1	-.079 (.364)	-.568 (.277)*	-.542 (.407)	-.809 (.312)**
	crim1 w1	.694 (.095)***	.598 (.038)***	.741 (.112)***	.578 (.049)***
American ID w3	ID w2	1.071 (.099)***	.921 (.054)***	1.068 (.094)***	.868 (.047)***
	crim1 w2	-.003 (.018)	-.018 (.015)	.006 (.017)	-.007 (.015)
crim1 w3	ID w2	-1.103 (.487)*	-.568 (.277)*	-1.407 (.554)*	-.809 (.312)**
	crim1 w2	.535 (.066)***	.598 (.038)***	.471 (.076)***	.578 (.049)***
ID-attitude trait covariance					
W1 ID-attitude covariance		-.054 (.023)*	-.055 (.023)*	-.055 (.023)*	-.059 (.023)*
W2 ID-attitude covariance		.033 (.021)	.053 (.027)*	.017 (.020)	.028 (.021)
W3 ID-attitude covariance		.023 (.017)	-.003 (.024)	.017 (.018)	.001 (.019)
CFI		1.000/.956	.999/ .961	1.000/.963	1.000/ .962
RMSEA		.000/.091	.009/ .060	.010/.110	.000/ .079
SRMR		.153	.146	.073	.062
Chisq (df)		3.760 (4)/ 12.903 (4)*	8.192 (8)/ 15.905 (8)*	4.099 (4)/ 17.130 (4)**	7.180 (8)/ 21.519 (8)**
Chisq test			4.432 (4)		3.081 (4)

Note: N = 272 for all models.

Note: Reported CFI, RMSEA, and χ^2 values are non-robust/robust.

[a] Warning: trouble constructing W matrix.